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How exposed are hedge funds to prime broker risk?

Magnus Dahlquist Simon Rottke Valeri Sokolovski*

July, 2025

Abstract

A small group of financial intermediaries manages over 90% of the hedge fund prime brokerage business, with prior research establishing shocks to these intermediaries as a systematic risk factor. We show that the average hedge fund's exposure to systematic financial intermediary risk exceeds the intermediary risk of its holdings. This heightened exposure is asymmetric, driven solely by negative aggregate shocks to financial intermediaries. In contrast, mutual funds and other risk factors show no similar effect. Examining idiosyncratic risk, we find that large adverse shocks to an individual prime broker only impact the performance of hedge funds using that broker exclusively, highlighting diversifiability of idiosyncratic shocks. Our findings underscore the unique risks of hedge funds due to their prime brokerage dependencies.

Keywords: Intermediary risk, Prime brokerage, Systematic risk, Idiosyncratic risk.
JEL codes: G12, G23, G24.

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1 Introduction

A recent report by the Bank for International Settlements highlights the potential risks lurking within the prime broker-hedge fund nexus (Araujo, Cohen, and Traco, 2024). While risks can theoretically flow in both directions, recent examples such as the collapse of Archegos Capital Management in March 2021 - which led to substantial losses for Credit Suisse, its main prime broker, due to inadequate risk management - did not produce any discernible systemic effects, suggesting that risks originating from hedge funds are less likely to pose a threat to the broader financial system.[1] In contrast, the transmission of risk from prime brokers to hedge funds appears more significant. Prime brokers, typically large investment banks, provide hedge fund clients with a range of services, most notably financing. In fact, over 50% of hedge fund leverage originates from prime brokers, much of it being short-term and susceptible to rapid withdrawal (see, e.g., Barth, Hammond, and Monin, 2020). Consequently, adverse shocks to prime brokers may transmit to hedge funds as funding pressure, compelling rapid de-leveraging, and potentially leading to fire-sale pricing and diminished performance (see, e.g., Brunnermeier and Pedersen, 2009; Liu and Mello, 2011; Mitchell and Pulvino, 2012; Adrian and Shin, 2013). A deeper understanding of these dynamics is crucial for both market participants and regulators, as hedge funds are often seen as the textbook arbitrageurs that keep the financial system running smoothly. It is especially important for hedge fund investors, who may be inadvertently exposed to excess financial intermediary risks through hedge fund prime broker relationships.

Prime broker shocks can be idiosyncratic, affecting a single prime broker, as seen with the detrimental impact of Lehman Brothers' bankruptcy on its hedge fund clients (Aragon and Strahan, 2012). Alternatively, these shocks can be systematic, impacting the entire prime brokerage sector. Importantly, we show that the prime brokerage industry is domi-

[1] See, for example, the report by the law firm Paul, Weiss on Credit Suisse's relationship with Archegos Capital Management. https://www.paulweiss.com/insights/client-news/credit-suisse-publishes-independent-review-of-archegos-losses

nated by a few key financial institutions, whose shocks have been shown to be a systematic risk factor affecting asset prices (He, Kelly, and Manela, 2017, hereafter HKM). Consequently, systematic prime broker shocks create a "nowhere to run" scenario, where hedge funds' asset holdings suffer from the systematic shock and their prime broker relationships become strained. The fact that the lion's share of prime brokerage services (particularly financing) is provided by a small group of systemically important banks creates a unique risk for hedge funds. In this paper, we examine the effects of both types of shocks – idiosyncratic prime broker shocks and systematic financial intermediary sector shocks – on hedge fund risks and returns. We find that while idiosyncratic shocks can be mitigated by diversifying across multiple brokers, hedge funds remain uniquely vulnerable to systematic prime broker risks, unlike mutual funds, which are not exposed to these pressures.

To assess the impact of systematic prime broker shocks, we first analyze the relationships between prime brokers and hedge funds to pinpoint the key players in the sector. Using a dataset that tracks hedge funds' prime broker affiliations over time, we note that a small group of prime brokers, those designated as New York Federal Reserve Primary Dealers, account for approximately 85% of hedge fund assets under management (AUM). In other words, several, large, systemically important financial intermediaries dominate the sector. Notably, prior literature has shown that aggregate shocks to these intermediaries represent a significant source of systematic risk. Specifically, HKM establish that shocks to the equity capital ratio of primary dealers (the HKM factor) are priced across a wide cross-section of base assets. Building on this, Dahlquist, Rottke, Sokolovski, and Svedrup (2025) show that the HKM factor also influences the cross-section of hedge fund returns.[2] Hence, hedge

[2]There are several other studies suggesting that financial intermediary risk matters for hedge fund returns. For example, Boyson, Stahel, and Stulz (2010) find that excess correlation of returns across hedge fund style indices increases significantly with large, adverse shocks to either a portfolio of prime broker firms or a portfolio of bank stocks. In line with this finding, Khandani and Lo (2007, 2011) show that many hedge funds experienced losses during the market-wide deleveraging in 2007. Additionally, Chen, Joslin, and Ni (2018) find that the tightening of the intermediary constraints predicts higher future excess returns for an aggregate hedge fund portfolio. Similarly, Billio, Getmansky, Lo, and Pelizzon (2012) study the connectedness between hedge funds, banks, broker/dealers, and insurance companies, finding that banks play the most important role in transmitting shocks to hedge funds. Additionally, Haddad and Muir (2021)

funds tend to be exposed to systematic financial intermediary risk, presumably mainly through their holdings.

We ask, however, whether hedge funds' systematic financial intermediary risk exposures are simply a reflection of the assets that funds hold, or whether this exposure is also driven by hedge funds' connection to prime brokers. In particular, using the HKM factor to capture systematic financial intermediary risk, we investigate whether hedge fund financial intermediary ex post beta is simply the weighted beta of their reported holdings, or if hedge funds are exposed to financial intermediary risk above and beyond their holdings. We posit that the excess financial intermediary beta stems from what we term the prime broker shock propagation channel. More specifically, if prime brokers compel hedge funds to adjust their positions during periods of prime broker distress via reductions in leverage financing, the hedge funds' ex post financial intermediary exposure will exceed what is implied by a simple buy-and-hold portfolio of their holdings.[3]

Essentially, we aim to identify the portion of a hedge fund's financial intermediary beta not reflected in the beta of its holdings, which we denote $\beta^{\text{PBCh.}}$, while accounting for leverage and short sales. For example, if a hedge fund is levered two to one and the aggregate financial intermediary beta of its holdings portfolio is 0.2 and its short positions' beta is zero, then the implied financial intermediary aggregate beta of its holdings is 0.4. However, if we estimate this fund's financial intermediary beta to be 0.5, then the excess 0.1 would be attributed to $\beta^{\text{PBCh.}}$, particularly if no significant excess beta is recorded for other risk factors using the same procedure. In other words, $\beta^{\text{PBCh.}}$ is computed after appropriate adjustments for leverage and short sales. In essence, after adjusting for leverage and short sales, this logic can be extended to betas with respect to any risk factor. To this end, we model hedge fund returns to establish testable predictions for financial intermediary betas under assumptions about short selling and leverage. Specifically, we show that, with only a

find that shocks to intermediary health predict hedge fund index returns.

[3]The mechanism is conceptually akin to Edelen (1999), who finds that compelled trades by mutual funds impact their returns.

few tractable identifying assumptions, we can estimate the average $\beta^{\text{PBCh.}}$ without granular data on hedge fund leverage or short sales.

Our empirical strategy, thus, seeks to identify the average excess financial intermediary beta in hedge funds. Due to the necessity of observing hedge fund holdings, we focus on the subset of hedge funds that file Form 13F with the Securities and Exchange Commission (SEC), i.e., primarily equity hedge funds. Hence, we estimate the average excess financial intermediary beta among these hedge funds. Subsequently, we perform a similar estimation for a control group of active equity mutual funds. These mutual funds are similar to equity hedge funds in many respects but are devoid of prime broker affiliations and are thus not expected to show similar excess financial intermediary exposure. By contrasting the estimates derived from hedge funds with those from mutual funds, we aim to identify the distinctive impact of prime brokers on hedge funds.

We find that hedge funds display a positive and significant excess financial intermediary beta, a pattern not observed in mutual funds. Specifically, our estimated average $\beta^{\text{PBCh.}}$ is statistically significant and constitutes around 12% of the cross-sectional standard deviation of the financial intermediary hedge fund holdings-implied beta. Given that the average financial intermediary exposure of hedge fund holdings is low, this excess beta effectively doubles the average financial intermediary exposure already inherent in hedge funds' long positions. In stark contrast, we find no such excess exposure among mutual funds. Notably, in line with economic intuition, we find no excess exposure to other equity risk factors like the Fama and French (1993) HML factor for either hedge funds or mutual funds, highlighting the unique role of financial intermediary risk.

Importantly, we find that this effect is strongly asymmetric, driven solely by adverse systematic prime broker shocks. Specifically, the average hedge fund's downside financial intermediary beta is both statistically significant and economically substantial, amounting to approximately 28% of the cross-sectional standard deviation of downside financial inter-

mediary hedge fund holdings-implied beta. To put this excess exposure into perspective, a two standard deviation adverse monthly shock to the HKM factor – a common scenario in risk models – would result in approximately a 62 bps additional monthly loss (around the average monthly return of hedge funds in our sample). In contrast, we do not detect any excess downside beta among mutual funds. This asymmetry is further highlighted by the absence of excess upside financial intermediary beta in both hedge funds and mutual funds. In essence, hedge funds experience a pronounced incremental negative impact during prime brokers' downturns, without corresponding benefits during their upswings. This aligns with the hypothesized mechanism of the prime broker shock propagation channel, where only negative prime broker shocks propagate to hedge fund clients. Moreover, the pronounced asymmetry of this response mitigates concerns that our observations are primarily influenced by hedge funds' unobserved holdings, as these holdings would need to be highly specific on average to produce such a distinct asymmetric reaction to systematic prime broker shocks. In line with this, we do not observe significant asymmetric exposures to other risk factors. In total, our results provide evidence in support of the prime broker shock propagation channel, underscoring its significant and asymmetric impact.

Lastly, to better understand the idiosyncratic risk component, we examine a panel of hedge funds around four events where a prime broker experienced a large, adverse idiosyncratic shock (including the Lehman bankruptcy). We find that these shocks significantly negatively impact the relative performance of their hedge fund clients. However, this negative effect is predominantly experienced by funds that rely solely on the affected prime broker. In contrast, hedge funds engaging multiple prime brokers do not show significant effects. This indicates that even the most severe idiosyncratic prime broker shocks can be diversified by using multiple brokers. In line with this finding, we observe a clear trend post-2008, with an increasing number of hedge funds affiliated with multiple prime brokers (Figure 1), suggesting a proactive stance by hedge fund managers in mitigating idiosyncratic prime broker risks.

Related literature

Our work contributes to three strands of the literature. First, we contribute to the relatively small but growing literature that examines the relationship between prime brokers and hedge funds. Aragon and Strahan (2012) show that Lehman prime brokerage clients were more likely to fail following Lehman's bankruptcy. However, they focus primarily on the effect of the Lehman bankruptcy on the liquidity of the stocks held by hedge funds rather than hedge fund performance. Moreover, in contrast to their work, we distinguish between hedge funds with a single prime broker and those with multiple, revealing that idiosyncratic prime broker shocks, even extreme ones like the Lehman bankruptcy, are primarily diversifiable. Relatedly, Boyarchenko, Eisenbach, Gupta, Shachar, and Van Tassel (2020) find that macro-prudential regulations implemented post-2014 resulted in clients of regulated prime brokers reducing their prime broker leverage levels and engaging more prime brokers. In the same spirit, Bittner and Jank (2025) find that hedge funds with a larger number of prime brokers, and thus potentially greater bargaining power, receive lower haircuts on their repo borrowings from their respective prime brokers. These patterns suggest a proactive stance by hedge funds towards potential prime broker funding shocks. This aligns well with our findings, which indicate the diversifiable and economically modest impact of individual prime broker shocks on hedge funds. Klaus and Rzepkowski (2009) argue that adverse prime broker shocks are passed on to their clients, but their analysis is restricted to a short sample period from before the Global Financial Crisis, and they do not differentiate between systematic and idiosyncratic financial intermediary risk. Chung and Kang (2016) find that individual hedge fund returns are correlated with the returns of a portfolio of hedge funds sharing the same prime broker. Our findings align with theirs in that we find that prime broker shocks can affect hedge fund clients. However, we differ substantially from their work by highlighting that (i) the effects are driven by large adverse prime broker shocks, (ii) the individual shocks are diversifiable, and (iii) that the first order effect stems from systematic shocks. Our work is complementary to Kruttli, Monin, and

Watugala (2022), who show that Deutsche Bank's hedge fund clients experienced a reduction in their borrowing after an adverse shock to the bank in 2015–2016. We draw upon their empirical findings that prime brokers in distress limit hedge fund clients' leverage, to aid the interpretation of our hypothesized mechanism behind the prime broker shock propagation channel.

Second, we contribute to the literature on financial intermediary asset pricing (see, e.g., He and Krishnamurthy, 2013; Adrian, Etula, and Muir, 2014; He et al., 2017; Haddad and Muir, 2021; Du, Hébert, and Huber, 2023; Fontaine, Garcia, and Gungor, 2025). Our findings that hedge funds exhibit excess systematic financial intermediary beta (in line with the prime broker shock propagation channel) offer a unique and novel perspective in the literature on how systematic financial intermediary risk propagates among hedge funds, highlighting the special nature of hedge funds and systematic financial intermediary risk.

Third, we contribute to the large literature on the drivers of hedge fund returns (see, e.g., Agarwal and Naik, 2004; Fung and Hsieh, 1997, 2001, 2004; Sadka, 2010; Agarwal, Ruenzi, and Weigert, 2017; Bali, Brown, and Caglayan, 2014; Buraschi, Kosowski, and Trojani, 2013; Cao, Chen, Liang, and Lo, 2013; Hu, Pan, and Wang, 2013; Klingler, 2022; Sadka, 2010; Teo, 2011). Our findings on the excess systematic financial intermediary beta in hedge funds identify a distinct characteristic of hedge funds that is absent in other asset classes.[4] Our empirical approach of contrasting holdings-implied returns with reported returns relates to the literature on mutual funds (see, e.g., Kacperczyk, Sialm, and Zheng, 2008) and the recent work of Agarwal, Ruenzi, and Weigert (2023) studying hedge fund performance. We, however, are the first to apply this methodology to studying differences in risk exposures of hedge funds and their holdings.

We also indirectly relate to the studies examining prime brokers' other roles, such as information sharing (Kumar, Mullally, Ray, and Tang, 2020), capital introduction (Obizhaeva,

[4]Our results that systematic financial intermediary risk is important and that idiosyncratic shocks are largely diversifiable is in line with the findings of Bali, Brown, and Caglayan (2012), highlighting the key role of systematic risk (and not residual risk) in hedge fund return determination.

2019), identification of top performing hedge funds (Aragon, Chung, and Kang, 2023), IPO allocations (Yang, Kazemi, and Sherman Getmansky, 2021), and studies of the economic effects of additional affiliations like Franzoni and Giannetti (2019), who find that hedge funds that are officially affiliated with financial conglomerates have more stable access to capital. We differ from these studies in that our focus is on the systematic and idiosyncratic financial intermediary risk.

2 A model of hedge fund returns

We decompose hedge funds returns to help guide our hypothesis development. We assume fund i's monthly observed realized excess return in month t, $r_{i,t}$, has three components:

$$r_{i,t} = c_i + \ell_i r^{\mathrm{P}}_{i,t} + r^{\mathrm{F}}_{i,t}. \tag{1}$$

The first component, c_i, represents fund i's fixed costs. The second component, $r^{\mathrm{P}}_{i,t}$, is the return of fund i's portfolio and $\ell_i \geq 1$ denotes fund leverage, which we assume is applied uniformly at the fund level to all its positions. The third component, $r^{\mathrm{F}}_{i,t}$, stems from the hypothesized forced intra-month trading, due to prime broker shocks. We further decompose these stochastic components to build economic intuition and highlight the impact of prime broker shocks on hedge fund returns.

The second component, the return of fund i's portfolio, is a combination of $r^{\mathrm{O}}_{i,t}$, $r^{\mathrm{U}}_{i,t}$, $r^{\mathrm{S}}_{i,t}$, and $r^{\mathrm{R}}_{i,t}$, which are fund i's excess returns on its observed long, unobserved long, unobserved short positions, and unobserved deliberate intra-month trades respectively:

$$r^{\mathrm{P}}_{i,t} = (1 - w^{\mathrm{U}}_i - w^{\mathrm{R}}_i) r^{\mathrm{O}}_{i,t} + w^{\mathrm{U}}_i r^{\mathrm{U}}_{i,t} + w^{\mathrm{R}}_i r^{\mathrm{R}}_{i,t} - \ell^{\mathrm{S}}_i r^{\mathrm{S}}_{i,t} \tag{2}$$

We regard $r^{\mathrm{O}}_{i,t}$, $r^{\mathrm{U}}_{i,t}$, and $r^{\mathrm{S}}_{i,t}$ as returns on portfolios that are rebalanced only at the beginning of each month t. Hence, if a fund does not trade between rebalancing dates, $r^{\mathrm{R}}_{i,t}$ and $r^{\mathrm{F}}_{i,t}$

are equal to zero. w_i^{U} denotes the share of fund's capital invested in unobserved long positions (w_i^{U} lies between zero and one), w_i^{R} is the share of the portfolio being turned over through deliberate rebalancing trades, and $\ell_i^{\mathrm{S}} \geq 0$ denotes the fund's short exposure (e.g., if $\ell_i^S = 1$ the fund is short \$1 for every \$1 it has invested in long positions). Such granular decomposition is necessary for the identification strategy that follows.

We hypothesize that $r_{i,t}^{\mathrm{F}}$ is driven by systematic and idiosyncratic prime broker shocks:

$$r_{i,t}^{\mathrm{F}} = \beta_i^{\mathrm{PBCh.}} f_t^{\mathrm{FI}} + \gamma_{i,j}^{\mathrm{IPBCh.}} f_t^{\mathrm{PBj}}, \tag{3}$$

where f_t^{FI} represents systematic prime broker shocks and f_t^{PBj} represents shocks to fund i's individual prime broker j. Intuitively, one can think of both $\beta_i^{\mathrm{PBCh.}} f_t^{\mathrm{FI}}$ and $\gamma_{i,j}^{\mathrm{IPBCh.}} f_t^{\mathrm{PBj}}$ arising due to intra-month trading resulting from margin financing adjustments. For example, an adverse shock to the prime broker sector (or its individual prime broker j) could result in a hedge fund being forced to unwind some of its positions at potentially unfavorable prices, affecting returns. Barth et al. (2020) find approximately 94% of total borrowing by equity hedge funds, which are the focus of our empirical analysis, originates from their prime brokers. Therefore, in the face of an adverse prime broker shock, these hedge funds are unlikely to easily substitute prime broker funding with an alternative source.

Combining equations (1), (2) and (3) yields:

$$r_{i,t} = c_i + \ell_i \left[(1 - w_i^{\mathrm{U}} - w_i^{\mathrm{R}}) r_{i,t}^{\mathrm{O}} + w_i^{\mathrm{U}} r_{i,t}^{\mathrm{U}} + w_i^{\mathrm{R}} r_{i,t}^{\mathrm{R}} - \ell_i^S r_{i,t}^{\mathrm{S}}\right] + \underbrace{\beta_i^{\mathrm{PBCh.}} f_t^{\mathrm{FI}}}_{\text{systematic. PB channel}} + \underbrace{\gamma_{i,j}^{\mathrm{IPBCh.}} f_t^{PBj}}_{\text{idiosyncr. PB channel}} \tag{4}$$

This paper aims to quantify the effects of systematic prime broker shocks, measured by their exposure $\beta_i^{\mathrm{PBCh.}}$, and idiosyncratic prime broker shocks, measured by their exposure $\gamma_{i,j}^{\mathrm{IPBCh.}}$, on hedge fund returns. Throughout, we will return to this model to discuss the assumptions necessary for identifying these quantities.

2.1 Systematic prime-broker shock propagation channel

We now examine whether hedge funds' financial intermediary systematic risk exposures are simply a mechanical reflection of the assets that funds hold, or whether this risk is also partially driven by hedge funds' relationships with prime brokers.

In particular, we analyze hedge fund ex post financial intermediary betas, asking whether the observed betas are in excess of what is implied by hedge fund holdings. Our hypothesis is that during periods of prime broker distress, if prime brokers force hedge funds to modify their positions, the resulting financial intermediary exposure for these hedge funds could surpass that implied by a passive buy-and-hold strategy of their holdings. To illustrate the proposed mechanism, consider a scenario where, at the start of the month, Hedge Fund X holds shares of Stock A. Assume that Stock A is not influenced by financial intermediary shocks, yet it undergoes a temporary, firm-specific downturn mid-month, which fully recovers by month's end. Ideally, as a long-term investor, the hedge fund manager would not alter her position in A. However, if during this period the prime brokers are hit by a systematic shock, prime brokers may, via margin calls, compel the manager to liquidate her position in A at a loss. Observing Hedge Fund X's realized returns for the month would lead us to conclude that it incurred financial intermediary risk exposure, contradicting the expected buy-and-hold returns of Stock A. This example suggests that hedge fund intra-month trading could be systematically influenced by prime broker shocks.

Our goal is to identify the portion of a hedge fund's financial intermediary beta not reflected in the beta of its holdings. We model hedge fund returns, taking into account short selling and leverage, to establish testable predictions for financial intermediary betas. Our empirical strategy identifies the excess financial intermediary beta among equity hedge funds and compares it with a control group of active equity mutual funds. Lacking prime broker affiliations, these mutual funds are expected not to exhibit comparable excess financial intermediary exposure. The detailed methodology and comprehensive results are

delineated below.

2.2 Identification strategy

Using equation (4) as a starting point, we let portfolio components' excess returns follow a reduced-form factor model:

$$r_{i,t}^{\mathrm{O}} = \beta_i^{\mathrm{O}} f_t^{\mathrm{FI}} + \epsilon_{i,t}^{\mathrm{O}}, \tag{5a}$$

$$r_{i,t}^{\mathrm{U}} = \beta_i^{\mathrm{U}} f_t^{\mathrm{FI}} + \epsilon_{i,t}^{\mathrm{U}}, \tag{5b}$$

$$r_{i,t}^{\mathrm{S}} = \beta_i^{\mathrm{S}} f_t^{\mathrm{FI}} + \epsilon_{i,t}^{\mathrm{S}}, \tag{5c}$$

$$r_{i,t}^{\mathrm{R}} = \beta_i^{\mathrm{R}} f_t^{\mathrm{FI}} + \epsilon_{i,t}^{\mathrm{R}}, \tag{5d}$$

where all the random shocks, $\epsilon_{i,t}^{\mathrm{O}}$, $\epsilon_{i,t}^{\mathrm{U}}$, $\epsilon_{i,t}^{\mathrm{S}}$, and $\epsilon_{i,t}^{\mathrm{R}}$ are orthogonal to f_t^{FI}. Also, all f_t^{PBj} for $j \in J$ from equation (3) are uncorrelated to f_t^{FI}.

In our baseline empirical implementation, we consider a two-factor representation with the market factor, f_t^{M}, and f_t^{FI}, but in the formulation above, we omit f_t^{M} to simplify the exposition.

From equations (4) and (5) we get that each fund's ex post beta on the financial intermediary factor, β_i, is given by:

$$\beta_i = \frac{\mathrm{Cov}\left(r_{i,t}, f_t^{\mathrm{FI}}\right)}{\mathrm{Var}\left(f_t^{\mathrm{FI}}\right)} = \ell_i \left[(1 - w_i^{\mathrm{U}} - w_i^{\mathrm{R}})\beta_i^{\mathrm{O}} + w_i^{\mathrm{U}}\beta_i^{\mathrm{U}} + w_i^{\mathrm{R}}\beta_i^{\mathrm{R}} - \ell_i^S \beta_i^{\mathrm{S}}\right] + \beta_i^{\mathrm{PBCh.}}. \tag{6}$$

In the following, our main object of interest is $\beta_i^{\mathrm{PBCh.}}$, that is the incremental financial intermediary beta, which we hypothesize is positive and arises due to prime broker-hedge fund connections. In other words, our null hypothesis is that $\beta_i^{\mathrm{PBCh.}} = 0$ and our alternative hypothesis is that $\beta_i^{\mathrm{PBCh.}} > 0$. Our approach is to measure the average $\beta_i^{\mathrm{PBCh.}}$ in the cross-

section of hedge funds.

To this end, we estimate the following cross-sectional regression:

$$\beta_i = a + b\beta_i^{\mathrm{O}} + \varepsilon_i, \tag{7}$$

where β_i (β_i^{O}) is the FI beta of the hedge fund (its observed holdings) returns. Empirically, we estimate both using time-series OLS regressions of $r_{i,t}$ (or $r_{i,t}^{\mathrm{O}}$) on f_t^{FI}. Importantly, as previously mentioned, we always estimate the incremental financial intermediary betas within a multi-factor framework that controls for f_t^{M}.

The OLS estimator of the slope is

$$\widehat{b} = \frac{\mathrm{Cov}\left(\beta_i, \beta_i^{\mathrm{O}}\right)}{\mathrm{Var}\left(\beta_i^{\mathrm{O}}\right)} = \frac{\mathrm{Cov}\left(\ell_i\left[(1 - w_i^{\mathrm{U}} - w_i^{\mathrm{R}})\beta_i^{\mathrm{O}} + w_i^{\mathrm{U}}\beta_i^{\mathrm{U}} + w_i^{\mathrm{R}}\beta_i^{\mathrm{R}} - \ell_i^{\mathrm{S}}\beta_i^{\mathrm{S}}\right] + \beta_i^{\mathrm{PBCh.}}, \beta_i^{\mathrm{O}}\right)}{\mathrm{Var}\left(\beta_i^{\mathrm{O}}\right)}. \tag{8}$$

In order to identify $\beta_i^{\mathrm{PBCh.}}$ we make the following assumptions:

$$\beta_i^S = s_i\left[(1 - w_i^{\mathrm{U}} - w_i^{\mathrm{R}})\beta_i^{\mathrm{O}} + w_i^{\mathrm{U}}\beta_i^{\mathrm{U}} + w_i^{\mathrm{R}}\beta_i^{\mathrm{R}}\right] + \zeta_i, \tag{9a}$$

$$\mathrm{Cov}\left(\beta_i^{\mathrm{U}}, \beta_i^{\mathrm{O}}\right) = 0, \tag{9b}$$

$$\mathrm{Cov}\left(\beta_i^{\mathrm{R}}, \beta_i^{\mathrm{O}}\right) = 0, \tag{9c}$$

$$\mathrm{Cov}\left(\beta_i^{\mathrm{PBCh.}}, \beta_i^{\mathrm{O}}\right) = 0. \tag{9d}$$

where s_i represents the proportion of long positions' beta that is hedged with short positions (e.g., if a fund aims to hedge all its long beta exposure, s_i would be equal to one), and ζ_i is the residual financial intermediary beta of fund i's short positions that is independent of its long positions. We assume that $\mathrm{E}\left(\zeta_i\right) = 0$, which implies that hedge funds, on average, hold no incremental short exposure to financial intermediary risk that is independent of their long positions. Assumption (9a) is motivated by two considerations. First, hedge funds, particularly equity hedge funds, are known to match their long and

short positions based on firm characteristics to offset systematic risk. The "pairs trading" strategy that is implemented by simultaneously going long and short in two similar firms is an example of this approach (see, e.g., Gatev, Goetzmann, and Rouwenhorst, 2006). Second, an assumption commonly made in empirical asset pricing, which is supported by evidence, is that factor betas depend on characteristics (see, e.g., Koijen and Yogo, 2019; Daniel, Mota, Rottke, and Santos, 2020). Therefore, if we assume that hedge funds short stocks resembling those they hold long, and that betas are driven by stock characteristics, then the betas of funds' short positions would correlate with those of their long positions, regardless of whether fund managers explicitly consider these betas when selecting their shorts. To align as closely as possible with the model's assumptions, we restrict our sample to equity long-short and long-bias funds managed by independent hedge fund firms, where the majority of long positions are observable, as will be discussed later in the paper.

Assumption (9b) posits that the financial intermediary betas of the observed long positions are, on average, independent of the betas of the unobserved long positions. A plausible alternative posits a positive correlation between the two betas, stemming from the potential specialization of hedge funds in certain types of firms, holding, for example, both equity and debt of the same firm. Our assumption, however, is conservative. We show in Appendix A that a positive covariance would bias our estimates towards zero, making it more challenging to detect a significant prime broker propagation effect. Equation (9c) assumes the same for unobserved deliberate rebalancing trades, i.e., β_i^{R}.

Assumption (9d) states that the financial intermediary betas of the observed long positions are, on average, independent of the incremental beta from the hedge-fund-prime-broker channel. This condition is consistent with the null hypothesis of no prime broker propagation effect. In sum, even though we cannot observe some of the hedge funds' positions, our identification strategy, under reasonable assumptions, enables us to estimate the average excess financial intermediary beta of hedge funds effectively.

We then have that

$$\widehat{b} = \bar{\ell}(1 - \bar{s}\bar{\ell}^{\mathrm{S}})(1 - \bar{w}^{\mathrm{U}} - \bar{w}^{\mathrm{R}}) \times \mathrm{AF}, \tag{10}$$

where the bar denotes a cross-sectional mean (e.g., $\bar{\ell}$ is the cross-sectional average fund leverage), and $\mathrm{AF} = \mathrm{Var}(\beta_i^{\mathrm{O}})/\mathrm{Var}(\widehat{\beta}_i^{\mathrm{O}}) \leq 1$ is the attenuation bias factor arising as the result of the regressor $\widehat{\beta}_i^{\mathrm{O}}$ being estimated.

The intercept estimator is given as

$$\begin{aligned} \widehat{a} &= \bar{\beta} - \widehat{b}\bar{\beta}^{\mathrm{O}} \\ &= \bar{\ell}(1 - \bar{\ell}^{\mathrm{S}}\bar{s})\left(\bar{w}^{\mathrm{U}}\bar{\beta}^{\mathrm{U}} + \bar{w}^{\mathrm{R}}\bar{\beta}^{\mathrm{R}}\right) - (1 - \mathrm{AF})\bar{\ell}\bar{\ell}^{\mathrm{S}}\bar{s}(1 - \bar{w}^{\mathrm{U}} - \bar{w}^{\mathrm{R}})\bar{\beta}^{\mathrm{O}} + \bar{\beta}^{\mathrm{PBCh.}}. \end{aligned} \tag{11}$$

From equation (11), we observe that the attenuation bias factor reduces the probability of detecting a positive $\widehat{a}$. Consequently, being as conservative as possible, we assume $\mathrm{AF} = 1$ when interpreting our main results. Given $\widehat{a}$ and our assumptions, the average incremental financial intermediary beta (prime-broker-channel beta) can be approximated by:

$$\bar{\beta}^{\mathrm{PBCh.}} = \widehat{a} - \bar{\ell}\left(1 - \bar{\ell}^{\mathrm{S}}\bar{s}\right)\left(\bar{w}^{\mathrm{U}}\bar{\beta}^{\mathrm{U}} + \bar{w}^{\mathrm{R}}\bar{\beta}^{\mathrm{R}}\right). \tag{12}$$

3 Data and measurement

3.1 Hedge fund data

We obtain monthly returns, AUM, and characteristics data on hedge funds from five leading commercial databases: BarclayHedge, CISD/Morningstar, Eurekahedge, HFR, and Lipper/TASS. We combine these data sources to create a comprehensive union database, capturing all hedge funds, both dead and alive, available in any of these five databases.[5]

[5]The specifics of this merging process are detailed in Internet Appendix IA.A.

Our sample period runs from January 2000 to June 2021.[6]

Following the literature, we apply several basic filters to the data. We consider only the hedge funds that report monthly net-of-fees returns and exclude all fund-of-funds. Following the procedure detailed in Almeida, Ardison, and Garcia (2020), we exclude funds with unusual return patterns, such as large amounts of consecutive equal returns and repeated "blocks" of returns (see, e.g., Straumann, 2009; Bollen and Pool, 2012, for further details on these data issues). We exclude funds that never report their currency, style, or AUM. When a hedge fund has multiple share classes, we consider only a single share class for each fund and aggregate their AUMs. Lastly, we require that each fund in the sample reports at least 24 monthly returns during our sample period. After applying these filters, our final sample is a panel of 16,160 unique hedge funds that are associated with 7,103 unique hedge fund managing companies (managers, hereafter).

Table 1 reports the summary statistics for the hedge fund excess returns and AUMs in our sample. All returns and AUMs are in USD. We report cross-sectional averages of each fund's average monthly excess returns and each fund's standard deviation of its monthly excess returns, which illustrates the typical performance of a hedge fund in our sample. Similarly, the AUM statistics (mean, median, 25 and 75 percentiles) are the time-series average of monthly cross-sectional statistics that aim to convey the typical cross-sectional AUM distribution of the funds in our sample. We also report the cross-sectional standard deviation of the average excess returns.

A typical hedge fund in our sample has an average annualized return (standard deviation) of 5.06% (15.04%), but the average performance varies across funds with the cross-sectional standard deviation of 10.91%. Significant size disparities exist among hedge funds in our sample, with the majority being relatively small. The median fund AUM is \$47 million with the interquartile range spanning from \$12 to \$181 million and only a moderate variation observed across time and styles. However, the presence of several large

[6]Due to inconsistent coverage, we exclude data from before 2000, in line with Teo (2009).

hedge funds inflates the average AUM to $348 million.

The databases provide information on hedge fund prime brokerage affiliations. However, each database version only reflects the most recent prime broker affiliations for each fund, preventing us from detecting historical shifts in affiliations. To address this, we prioritize a sub-sample of hedge funds from the Eurekahedge database for analyses requiring timely prime broker data (specifically, event studies). This database enables tracking of affiliations over time. Specifically, we obtain additional database snapshots biannually (in June and December) from 2006 to 2017 and an additional one for June 2021. Since the data on each fund's prime brokerage affiliation is updated every six months, we minimize misclassification of prime brokerage affiliations throughout our sample period. The Eurekahedge database is regarded as representative and is solely employed by Hombert and Thesmar (2014) for its empirical investigations. Table 1 additionally presents summary statistics for our Eurekahedge sample. We note that the performance and AUM metrics closely align with the full union database, with only the mean AUM being smaller, as our union database contains a few more of the mega hedge funds. Nevertheless, to retain sufficient statistical power for one of our manager-level tests, which is already quite restrictive due to the requirement of holdings data and other filters, we supplement our sample with mostly static information on prime broker affiliation from the other four hedge fund databases.[7]

3.2 Hedge fund equity holdings data

For our analysis of the systematic prime-broker shock propagation channel in Section 2.1, we obtain quarterly hedge fund US equity holdings from Thomson Reuters' 13F holdings database. Since Form 13F is filed at the manager level rather than for individual funds, we aggregate the hedge fund returns and AUM, as previously described, to the manager level. Internet Appendix IA.A provides details on merging 13F managers with manager-level data

[7]For example, we also have four snapshots of the TASS database from 2010, 2012, 2015, and 2017, which allow us to augment the static information with some temporal variation for the TASS hedge funds.

from our union hedge fund database.

3.3 Mutual fund data

We source data on mutual funds returns, characteristics, and holdings from the Center for Research in Security Prices (CRSP) spanning July 2006 to June 2021. We consolidate share classes following Berk and Van Binsbergen (2015). We adjust for reported fees to compute gross returns. Additionally, we exclude funds not categorized under CRSP objective codes: sector, growth, income, or income & growth. We also omit passive funds and those with an absolute value of the log of the ratio of reported value of holdings to AUM larger than log(2), to avoid results being driven by funds who rely on a lot of leverage or positions not covered by 13F. We ensure each fund has at least 24 valid observations with both reported and holdings-based returns.

3.4 Stocks and factor data

Data on stock returns and prices are from CRSP. We integrate these with hedge fund 13F holdings using CUSIPs. Similarly, using the provided PERMNOs, we merge the CRSP stock data with CRSP mutual fund holdings. The intermediary factor data of He et al. (2017) is from Asaf Manela's webpage. The seven Fung and Hsieh (2004) factors are from Datastream and David A. Hsieh's Hedge Fund Data Library. The risk-free rate and Fama and French (1993, 2015) factor data are from Ken French's data library.

3.5 Sample selection and descriptive statistics

Our approach to estimating $\beta_i^{\text{PBCh.}}$ involves comparing hedge funds with mutual funds (our control group), under the expectation that mutual funds' financial intermediary risk is entirely determined by their holdings, unaffected by the prime broker channel. To facilitate comparison to mutual funds and ease of interpretation, we concentrate on a uniform group

of independent hedge fund managers where we can observe most of their long positions. In particular, we consider only the managers with, at most, five individual hedge funds, all of which must have a global or North American investment focus and predominantly invest in equities (as identified by their style, such as "Long-Short Equities" or "Equity Market Neutral"). Moreover, we require the time-series median of the ratio of holdings market value to reported manager AUM to lie between 0.2 and 5.[8] Lastly, we require 24 months of data, to estimate betas. After implementing these filters, we arrive at our final sample of 523 hedge fund managers.[9]

Table 3 presents the descriptive statistics for our sample of hedge funds (Panel A), and our sample of US mutual funds (Panel B) that we use as a control group. We observe, on average, around eight years of returns for each hedge fund, and around seven years of returns for each mutual fund. The average (median) hedge fund size is around \$409 (\$216) million. The average mutual fund size is larger (\$984 million) due to the presence of a few mega funds, but the median mutual fund is of similar size to that of hedge funds (\$206 million). The average (median) number of stocks held by hedge funds is 74 (40), while mutual funds typically hold slightly more stocks in their portfolios, with the average (median) holdings being 90 (61) stocks. The average (median) ratio of holdings market value to reported AUM (TNA Ratio) is 1.41 (1.00) for hedge funds, implying that hedge funds typically use some leverage. In contrast, the average (median) TNA Ratio of mutual funds is 0.94 (0.96), implying that equity mutual funds do not use leverage and remain fully invested except for a small liquidity cushion of around 6% of AUM. We find that the average (median) stock turnover in hedge funds is around 22% (20%) per quarter and is only 11% (9%) in mutual funds, which is consistent with economic intuition as hedge funds are considered more active traders.

We also report descriptive statistics for the holdings and fund (reported) return betas.

[8]Internet Appendix IA.A provides details on the hedge fund sample selection.

[9]In Table IA.1 in the Internet Appendix, we confirm that our main empirical results are similar if we instead consider all the 1,305 matched managers with 13F filings.

The betas are estimated using a two-factor model, with the market as the first factor and either financial intermediary (FI) factor or Fama and French (1993) HML as the second factor. We use the HML factor as a placebo in our main analysis. As anticipated, the average holdings-implied market beta is approximately 1, aligning precisely for mutual funds, which typically mirror the market portfolio. The average market beta for hedge fund holdings is slightly higher at 1.12, indicating a propensity for going long stocks with higher betas. The average fund market beta for mutual funds is essentially identical to their average holdings beta (0.96). In contrast, the average fund market beta for hedge funds is only 0.48, demonstrating the effect of short positions. For mutual funds, the holdings and fund FI betas are 0.013 and 0.010, respectively. Lastly, hedge funds show slightly larger FI holdings betas at 0.016 and notably higher fund betas at 0.026.

3.6 Measuring systematic prime broker risk

Measuring systematic prime broker risk requires identifying the most influential entities in the prime brokerage space. We begin by analyzing the structure of the prime brokerage market to determine the key players. Table 2 presents the market share of leading prime brokers over time. While our database contains around 480 unique prime broker names, the top 10 and 20 prime brokers (that are all publicly listed companies), on average, account for around 86% and 95% of total hedge fund AUM, respectively. Moreover, we find a high degree of persistence in the relative importance of specific prime brokers. For example, Goldman Sachs and Morgan Stanley are almost always ranked first or second.[10] Notably, despite using a different approach to identify the most important financial intermediaries, we converge on a very similar group of intermediaries as He et al. (2017) who consider the primary dealers as a set of key financial intermediaries for their empirical analysis, finding

[10]This pattern is consistent with Aragon and Strahan (2012), who report prime broker market shares between 2002 and 2008, and similar to Di Maggio, Kermani, and Song (2017) and Eisfeldt, Herskovic, Rajan, and Siriwardane (2023), who respectively find that the market structure in the credit default swap and bond dealer markets is highly persistent.

that their empirical intermediary's equity capital ratio factor affects a large cross section of asset classes.[11] The primary dealers capture, on average, around 87% of total hedge fund AUM, and, throughout the years, nearly all the top 10 prime brokers are consistently designated as primary dealers. Given these findings, and to better align with the existing literature, we adopt He et al. (2017)'s financial intermediary factor as our measure of systematic prime broker sector risk (PB, hereafter).[12] We note that constructing our own systematic prime broker factor, using either value- or equal-weighted portfolio of the listed prime brokers in our sample, yields very similar results, which is expected given the high correlation (over 0.95) between our constructed factor and HKM (see Table IA.2 in the Internet Appendix). Hence, we consider the use of the HKM factor to be appropriate.

3.7 Variable construction

The two key observed quantities necessary for our empirical estimation strategy are $r_{i,t}$ and $r_{i,t}^{\mathrm{O}}$. For $r_{i,t}$, we use each fund's reported net returns in excess of the risk-free rate, $r_{f,t}$. Given that hedge fund holdings are reported at the manager level, in the event that a manager has multiple funds, $r_{i,t}$ is computed as an asset-weighted reported portfolio excess return of each manager's individual funds. For $r_{i,t}^{\mathrm{O}}$, following Kacperczyk et al. (2008), we define it as the total excess return on a hypothetical buy-and-hold portfolio based on the most recently disclosed stock positions.

$$r_{i,t}^{\mathrm{O}} = \sum_{j=1}^{n} \tilde{w}_{j,t-1} r_{j,t} - r_{f,t}, \tag{13}$$

where $r_{j,t}$ is a monthly return for stock j, and $\tilde{w}_{j,t-1}$ is the weight of stock j in a fund's portfolio. The weights depend on the number of shares held by the fund at the most recent

[11] Primary dealers are a natural group to consider as there is ample evidence suggesting that they account for the bulk of trading in many markets (see, e.g., Cetorelli, Hirtle, Morgan, Peristiani, and Santos, 2007).

[12] He et al. (2017)'s financial intermediary factor is defined as intermediary capital ratio innovations. The intermediary capital ratio is constructed as the total primary dealer market equity divided by total assets (total market equity plus total book debt of the primary dealers).

disclosure data at time $t-\tau$, $N_{j,t-\tau}$, and the stock price at the end of the previous month, $P_{j,t-1}$ (adjusted for stock splits and other share adjustments when necessary):

$$\tilde{w}_{j,t-1} = \frac{N_{j,t-\tau} P_{j,t-1}}{\sum_j^n N_{j,t-\tau} P_{j,t-1}}. \tag{14}$$

4 Prime broker channel empirical results

Equation (12) implies that, to establish evidence of the prime broker shock propagation channel, the hypothesis to be tested is as follows:

$$\begin{aligned} H_0 &: \widehat{\beta}^{\text{PBCh.}} \equiv \widehat{a} - \bar{\ell}\left(1 - \bar{\ell}^{\text{S}}\bar{s}\right)\left(\bar{w}^{\text{U}}\bar{\beta}^{\text{U}} + \bar{w}^{\text{R}}\bar{\beta}^{\text{R}}\right) = 0 \\ H_1 &: \widehat{\beta}^{\text{PBCh.}} \equiv \widehat{a} - \bar{\ell}\left(1 - \bar{\ell}^{\text{S}}\bar{s}\right)\left(\bar{w}^{\text{U}}\bar{\beta}^{\text{U}} + \bar{w}^{\text{R}}\bar{\beta}^{\text{R}}\right) > 0. \end{aligned}$$

In other words, the estimated intercept, $\widehat{a}$, needs to be both positive and sufficiently large. To test this hypothesis, we require values for the different parameters. For our benchmark results, we choose economically reasonable parameters based on existing literature and descriptive statistics, but verify that our results are robust to different choices for the values of these parameters (see subsection 4.2 for a detailed discussion).

4.1 Empirical results

Panel A of Table 4 presents the empirical results from regression (7). In the first step, we estimate full-sample time-series regressions separately for each hedge fund's reported excess returns and corresponding holdings-based excess returns using a two-factor model that includes MKT and FI. We save the estimated FI betas from both regressions. In the second step, we implement regression (7) using weighted least squares (WLS), where each observation is weighted by the number of monthly return observations used to estimate the corresponding beta. This weighting scheme ensures that more precise beta estimates

(i.e., those based on longer return histories) receive greater emphasis in the cross-sectional analysis.[13]

We report the results for all the test variations separately for hedge funds and mutual funds. We find that, for hedge funds, $\widehat{\beta}^{\text{PBCh.}}$ is positive, equal to 0.020, and statistically significant at the 1% level (i.e., the estimated $\widehat{a}$ exceeds the parameterized model implied intercept under the null). This indicates that hedge funds, on average, possess additional exposure to financial intermediary risk above and beyond their holdings. In contrast, mutual funds exhibit no such extra exposure. To assess the economic significance, we contrast $\widehat{\beta}^{\text{PBCh.}}$ with the standard deviation of the holdings' FI betas, and evaluate the hypothetical impact of $\widehat{\beta}^{\text{PBCh.}}$ on fund performance given a 2-σ monthly shock to the FI factor. The latter is advantageous as it facilitates comparability between hedge funds and mutual funds and is independent of the data used in the estimation. For hedge funds, $\widehat{\beta}^{\text{PBCh.}}$ constitutes approximately 11.6% of the standard deviation of hedge fund holdings' FI beta. Additionally, the estimated excess exposure implies that a 2-σ adverse monthly shock to the FI factor leads a 27 bps excess loss, which amounts to 46% of an average monthly return of a hedge fund in our sample. This indicates an economically meaningful excess FI beta, which is consistent with a prime broker shock propagation channel.

We posit that the prime broker shock propagation channel, if present, would mainly manifest through negative shocks to financial intermediaries, indicating an asymmetric effect. Specifically, prime brokers, during periods of adverse shocks, could induce hedge funds to adjust their positions via margin calls and other funding pressures. It is, however, unlikely that prime brokers could as seamlessly induce hedge funds to trade during good periods by extending them additional credit and services. To investigate this, we partition the analysis, estimating downside betas from months with negative FI factor returns and upside betas from those with positive returns. Considering first the downside FI betas, we

[13]The results from OLS estimation are reported in Table IA.3 in the Internet Appendix and are very similar.

observe for hedge funds positive and economically large $\widehat{a}$ (0.083), which is more than four times greater than the model implied intercept. The difference, i.e., downside $\widehat{\beta}^{\text{PBCh.}}$, is statistically significant (p-value < 0.001) and constitutes 27.7% of the standard deviation of hedge fund holdings downside FI beta. Moreover, this excess downside exposure implies a 62 bps loss in the event of a 2-σ adverse monthly FI factor shock, amounting to 105% of an average hedge fund monthly return. In other words, this excess downside exposure to financial intermediary risk appears economically meaningful. In stark contrast, mutual funds show an $\widehat{a}$ that is also positive but over ten times smaller than that of hedge funds, and it is not statistically greater than the model implied intercept (p-value $= 0.629$). Notably, when analyzing upside FI betas, we identify negligible and negative $\widehat{a}$ that are consistent across both mutual funds and hedge funds. These asymmetrical outcomes support our hypothesis that hedge funds' additional exposure to financial intermediary risk occurs exclusively via negative shocks to financial intermediaries. Hedge funds notably incur negative impacts during periods of prime brokers' distress, yet do not equally benefit from positive shocks in prime broker performance. This is in line with the prime broker shock propagation channel.

Our model also makes predictions about the estimated slope coefficient, as outlined in equation (10). To verify the consistency of our estimates given our chosen parameter values, we compare the estimated slope $\widehat{b}$ with the parameterized model's implied slope, which is derived independently of the factor model. For hedge funds, the parameterized model-implied slope is 0.520, closely matched by the estimated $\widehat{b}$, which ranges from 0.512 to 0.574 across different specifications. This suggests that our chosen parameter values are reasonable. Nevertheless, we conduct some sensitivity analysis of our estimates using different parameter values, ascertaining that our principal conclusions remain essentially unaffected by all reasonable selections of the model's parameters (we discuss these results in the next sub-section).

Placebo factors We conduct a placebo test, repeating our entire analysis by replacing the FI factor with the Fama-French value factor HML (Panel B of Table 4). Our expectations are that neither hedge funds nor mutual funds should have systematically larger exposure to HML above and beyond their holdings. As previously mentioned, our tests necessitate assumptions about certain parameters, particularly $\bar{\beta}^{U}$, the average exposure of unobserved positions. We posit that the average HML holdings beta serves as a reasonable proxy for $\bar{\beta}^{U}$. It is unlikely that the HML exposures of hedge funds' unobserved positions would systematically deviate from those of their observed positions, rendering HML a suitable factor for a placebo test.

Additionally, the HML factor is a long-short portfolio and thereby approximately orthogonal to the market factor, reducing concerns about multicollinearity in this test. In line with our intuition, we find that $\widehat{a}$ is never greater than the model implied intercept for hedge funds or mutual funds.

We also consider additional placebo factors, including the Fama-French SMB (Small Minus Big), CMA (Conservative Minus Aggressive), and RMW (Robust Minus Weak) factors, as well as the momentum factor (MOM). The results are reported in Internet Appendix Table IA.4. While it is possible that differences in hedge fund holdings and return-based exposures for these factors may reflect variation in unobserved positions, none of them exhibit the distinctive pattern we observe with the FI factor. Specifically, only the FI factor shows significantly higher return-based exposure relative to holdings-based beta, with this difference concentrated in the downside-beta subsample and absent in the upside-beta subsample, a pattern not replicated with any of the other factors.

Potential multicollinearity Since MKT and the FI factor are correlated, multicollinearity could be a concern. To assess its potential impact, we consider a specification where we first regress te FI factor on MKT, save the residuals, and then include these residuals as a second factor in the augmented market model. This stricter specification creates a lower

bound for the true effect, as all common variation is, by construction, attributed to MKT, leaving only FI-specific shocks. The results of this specification are reported in Internet Appendix Table IA.5 and are similar to those from the benchmark model.

Alternative null models We also verify that our results are robust to alternative models used to estimate financial intermediary betas. The results for the hedge fund sample are presented in Table 5 and the results for the mutual fund sample is reported in Internet Appendix Table IA.6. First, we consider the Fama and French (2015) five-factor model augmented with the FI factor (Panel A). Next, we explore two models that incorporate controls for liquidity. Specifically, we estimate a market model augmented with the Pástor and Stambaugh (2003) illiquidity factor, which captures market-wide liquidity shocks, along with the FI factor (Panel B). We also estimate a market model augmented with the TED spread, commonly used to proxy for broad funding liquidity shocks (see, e.g., Brunnermeier, Nagel, and Pedersen, 2009)), again including the FI factor (Panel C). Our findings remain consistent across these specifications, suggesting that alternative risk factors are unlikely to be driving the results.

Controlling for idiosyncratic prime broker shocks Lastly, we examine whether our results could be driven by idiosyncratic shocks to individual prime brokers rather than by systematic shocks to the broader prime broker sector. To test this, we augment the model used to estimate financial intermediary betas by including the excess returns of each fund's individual prime brokers (when available) as an additional factor.[14] Recalling that in the first stage we estimate FI betas using both hedge fund holdings and reported hedge

[14]Our analysis is conducted at the fund manager level. Prime broker affiliation is reported at the fund level for a subset of funds. To assign each manager a prime broker, we match the manager to the prime broker(s) associated with the fund(s) they manage. When a manager oversees multiple funds, or when multiple prime brokers are listed, we compute a value-weighted average of the prime broker returns using the respective fund AUMs as weights. We prioritize prime broker information from Eurekahedge when available; otherwise, we use any other available data source. To maximize coverage, we also consult duplicate fund entries, i.e., alternative share classes or fund versions excluded from the main sample (e.g., due to shorter return histories), to extract prime broker information if it is missing from the main entry.

fund returns, we interpret a higher FI beta on reported returns (relative to holdings) as evidence of a systematic hedge fund prime broker channel. However, it is possible that the higher FI beta on reported returns is partially capturing exposure to the fund's individual prime broker, an effect omitted in the baseline specification. By including excess returns of the individual prime brokers as additional controls, we can test this possibility. If the channel is primarily driven by idiosyncratic prime broker shocks, the estimated FI beta on hedge fund returns (as well as the gap between returns-based and holdings-based FI betas) should decrease in absolute magnitude, with the idiosyncratic prime broker control absorbing the relevant exposure. We report the results in Panel D of Table 5. We observe little effect on the $\widehat{\beta}^{\text{PBCh.}}$ estimate in either the standard or the downward beta specification: $\widehat{\beta}^{\text{PBCh.}}$ remains both statistically and economically significant. We note that the sample is reduced to 252 funds due to the availability of prime broker affiliation data. To assess the impact of this sample restriction, we re-estimate our baseline results on the restricted sample and find slightly higher estimates of $\widehat{\beta}^{\text{PBCh.}}$ for β^{FI} (0.023) and β^{FI}_{down} (0.069) than in the main specification (see Internet Appendix Table IA.7). Comparing these to the estimates that include individual prime broker controls from Panel D of Table 5, the point estimates of $\widehat{\beta}^{\text{PBCh.}}$ decline by approximately 10% when we control for individual prime broker risks (although these differences are not statistically significant). This suggests that, while idiosyncratic prime broker shocks may contribute to some variation, the majority of the effect is driven by systematic prime broker shocks. In the next section, we investigate the role of individual prime broker shocks more directly by conducting a series of event studies around major adverse shocks to specific prime brokers.

Summary The empirical evidence presented confirms the impact of the prime broker shock propagation channel on hedge funds. The significant positive $\widehat{\beta}^{\text{PBCh.}}$ for hedge funds indicates an additional exposure to financial intermediary risk, which extends beyond what their holdings alone can explain, and is particularly evident during negative financial in-

termediary shocks. In contrast, mutual funds do not exhibit similar excess exposure. The asymmetry in this risk exposure is highlighted by the distinct downside FI betas for hedge funds compared to those for mutual funds. Placebo tests using other known factors further validate the unique nature of hedge funds' financial intermediary risk exposure. Importantly, our findings remain robust across a range of alternative null models, including specifications that control for market-wide liquidity and funding conditions, confirming that our results are not driven by other known sources of systematic risk. Finally, controlling for idiosyncratic shocks to individual prime brokers, by augmenting the factor model with prime broker-specific excess returns, leads to only a modest decline in the estimated $\widehat{\beta}^{\text{PBCh.}}$, suggesting that the observed effects are largely attributable to systematic, rather than idiosyncratic, prime broker shocks.

4.2 Robustness of model parameter choices

In this subsection, we examine the robustness of our findings by testing the sensitivity of our results to variations in key model parameters, ensuring that our conclusions hold across a range of economically reasonable choices.

For our benchmark results, we use the findings of Barth et al. (2020), who study leverage dynamics of hedge funds utilizing comprehensive regulatory data, to guide our choice of $\bar{\ell}$ and $\bar{\ell}^{\text{S}}$. They find that an average equity hedge fund's gross leverage is 1.57, and it has around \$0.57 (= 0.89/1.57) of short positions for every \$1 in long positions. We therefore choose $\bar{\ell}$ and $\bar{\ell}^{\text{S}}$ to be 1.57 and 0.57, respectively. We choose $\bar{s} = 1$, assuming that hedge funds, on average, aim to perfectly match the risk exposures of their long and short positions (we verify that our results are robust to smaller values of $\bar{s}$). Guided by our summary statistics we choose $\bar{w}^{\text{R}} = 0.11$. Our choice is based on monthly turnover of around 11% (i.e., rebalancing). For $\bar{w}^{\text{R}}$ we make an assumption that, on average, around 12% of hedge fund assets remain unobserved i.e., $\bar{w}^{\text{R}} = 0.12$. In particular, using 13F holdings, we find

that on average, 6% of mutual fund positions remain unobserved, likely due to them being held in cash or short-term risk-free debt to manage liquidity and to take advantage of short-term market timing opportunities. We assume that this unobserved portion is twice as high for hedge funds, i.e., around 12% of AUM. Lastly, we choose $\bar{\beta}^{\mathrm{U}} = \bar{\beta}^{\mathrm{R}} = 0.016$ (0.115 for downside beta, and 0.072 for upside beta), which is equal to the average hedge fund holdings beta (we assume that the unobserved positions – both from the beginning of the month and those that originate from deliberate intra-month trades – stem from the same universe as the observed). For mutual funds the choice is simpler, as they, on average, neither short nor use leverage i.e., $\bar{\ell}$ and $\bar{\ell}^{\mathrm{S}}$ are one and zero, respectively. Hence, we only need to choose the values of $\bar{\beta}^{\mathrm{U}}$, $\bar{\beta}^{\mathrm{R}}$ as well as $\bar{w}^{\mathrm{U}}$ and $\bar{w}^{\mathrm{R}}$. We set $\bar{\beta}^{\mathrm{U}} = \bar{\beta}^{\mathrm{R}} = 0.013$ (average mutual fund holdings FI beta; 0.066 for downside beta, and 0.005 for upside beta) and set $\bar{w}^{\mathrm{U}} = 0.06$ (unobserved positions of 6%) and $\bar{w}^{\mathrm{R}} = 0.055$ (expected monthly turnover of 5.5%).

We verify that our results are not sensitive to these parameter choices. In particular, we vary the parameters representing the average share invested in unobserved positions ($\bar{w}^{\mathrm{U}}$) and average proportion of a long position's beta hedged with short position ($\bar{s}$), as we do not have precise estimates for these parameters.[15] Figure 2 presents the results. We observe that increasing $\bar{\omega}$ increases the model-implied intercept. However, unrealistically high values of $\bar{\omega}$ would be needed in order to get $p-$values north of conventional levels of statistical significance ($\bar{\omega} \geq 0.95$ for full-sample betas and $\bar{\omega} \geq 0.66$ for downside betas to surpass a significance level of 1%). In the same spirit, decreasing $\bar{s}$ also increases the model-implied intercept. However, even setting $\bar{s} = 0$ still leaves the empirical estimate of a significantly larger than the model-implied one.

Although we have reliable estimates from Barth et al. (2020) for $\bar{\ell}$ and $\bar{\ell}^{\mathrm{S}}$ (representing the average hedge fund leverage and the average long/short ratio, respectively), we include these parameters in our sensitivity analysis. Figure 2 present those results. We observe

[15] We note that for ease of exposition, we consider $\bar{w}$ defined as $\bar{w} = \bar{w}^{\mathrm{U}} + \bar{w}^{\mathrm{R}}$ from Equation (12).

that increasing $\bar{\ell}$ raises the model-implied intercept. However, even at $\bar{\ell} = 2.59$, which corresponds to the 90th percentile of hedge fund leverage reported by Barth et al. (2020), the model-implied value of a remains far below the empirically estimated one. Similarly, decreasing $\bar{\ell}^{\text{S}}$ also increases the model-implied intercept. Yet, even when $\bar{\ell}^{\text{S}}$ is set to 0, the empirical estimate of a is still significantly larger than the model-implied value.

In summary, while our identification strategy relies on assumptions for several parameters, our sensitivity analysis demonstrates that the main conclusions are robust to reasonable variations in these choices. This reinforces the reliability of our findings across a spectrum of economically plausible scenarios.

Moreover, we want to emphasize that our results can be thought of as a lower bound on the true effect size, as we conservatively assumed the attenuation bias factor to be AF = 1, i.e., the maximum value it can possibly take. For any value AF < 1, the results would become stronger (see equation (11)).

5 Event study of individual prime broker shocks

In this section, we investigate how shocks to individual prime brokers impact the performance of their hedge fund clients. In other words, we seek to determine whether shocks from an individual prime broker are transmitted to its hedge fund clients. Recalling equation 4, we now focus on the effect of $\gamma_{i,j}^{\text{IPBCh.}}$ i.e., hedge fund exposure to idiosyncratic shocks of its own prime broker. We posit that it is predominantly the largest adverse shocks to an individual prime broker that are likely to affect its clients. Specifically, following a large adverse shock, a prime broker may need to limit the liquidity available to its clients and possibly temporarily reduce the quality of other services as it reallocates its constrained resources. This can adversely affect its clients' operations and performance. To identify this potential effect, we focus on four well-publicized events that represent large adverse shocks to specific prime brokers and examine how these events influenced the performance

of their hedge fund clients.

5.1 Prime broker events

We begin by looking at the Lehman bankruptcy on 15 September 2008. Figure 4 presents the proportion of Lehman's hedge fund clients that reported returns to the Eurekahedge database in July 2008 and continued to do so in subsequent months. By January 2009, 28% of the Lehman-affiliated funds from July 2008 no longer reported returns to the database. In stark contrast, during the same period, only 4% of the matched group of hedge funds stopped reporting.[16] This finding is in line with Aragon and Strahan (2012), who also find that Lehman-affiliated funds disappeared from the database at a higher rate than other hedge funds. While there are multiple reasons for discontinuing performance reporting, it is reasonable to assume that, during a crisis, numerous hedge funds exit the database due to markedly poor performance or liquidation. Lo, Getmansky, and Mei (2004) contend that over 90% of non-reporting funds are ultimately liquidated. Hence, we interpret these results as a higher failure rate of Lehman clients.

In contrast to previous studies, we categorize Lehman-affiliated hedge funds into two groups: those who used Lehman as their sole prime broker at the time of its bankruptcy, and those who used it alongside other brokers. We hypothesize that prime broker shocks could differently affect hedge funds that are its sole clients. Specifically, funds with multiple prime brokers might be less susceptible to an adverse shock from a single prime broker, given their ability to diversify their funding and operational needs across prime brokers. Figure 4 shows that a staggering 40% of Lehman clients that used Lehman as their sole prime broker were liquidated, compared to just 4% of the matched group. Notably, 21% of Lehman clients with a single prime broker ceased operations in September 2008. In

[16]The matched group comprises hedge funds that had affiliations with prime brokers other than Lehman. Each Lehman hedge fund client that reported to the database in July 2008 is matched to another hedge fund (without replacement) based on the number of prime brokers, style, AUM, and returns over the last 12 months leading up to July 2008.

contrast, none of Lehman clients with multiple prime brokers were affected in September and only 12% had subsequently disappeared by January 2009, with zero exits observed in the matched group. Thus, while Lehman clients with multiple prime brokers experienced disruptions following the bankruptcy, their resilience was markedly higher than that of funds affiliated solely with Lehman.

Next, we examine other large, but less extreme, adverse shocks to individual prime brokers, in contrast to the extreme case of Lehman's bankruptcy. Specifically, we consider the March 2008 Bear Stearns failure,[17] the September 2011 UBS rogue trader trading loss,[18] and the April 2012 J.P. Morgan trading loss.[19] Our sample provides reasonable coverage of the affected hedge funds: it comprises 169 Bear Stearn clients, 260 UBS clients, and 201 J.P. Morgan clients during the respective events. Examining the affected brokers' clients' risk adjusted returns around the time of the event, we observe trends that align with our analysis of hedge fund performance during the Lehman bankruptcy. Specifically, hedge funds using an affected prime broker as their sole prime broker underperformed relative to their peers, whereas funds with multiple prime brokers showed no distinct performance deviation from the matched group.[20]

[17]The Lehman and Bear Stearns events are both extreme events in the sense that, in each case, both prime brokers ceased to exist after the event. However, the Bear Stearns failure and subsequent sale to J.P. Morgan was a more controlled termination than that of Lehman (see, e.g., Brunnermeier, 2009).

[18]In September 2011 UBS reported a USD 2.3 billion loss caused by a rogue trader who was subsequently jailed. The loss amounted to approximately 4% of UBS's equity capital, was widely scrutinized by the press, and led to the resignation of the company's CEO. UBS's stock return was −20% in September 2011.

[19]On 27 April 2012 J.P. Morgan delayed the filing of the quarterly SEC form 10-Q. On 10 May 2012, during an investor conference call, J.P. Morgan management announced a $2 billion trading loss. The loss was reportedly caused by a London-based trader's position in CDS (so called London "whale"). The total size of the loss was subsequently updated to be around $7.5 billion and accounted for around 4% of J.P. Morgan's equity capital. The loss attracted substantial media attention and triggered an investigation by the Federal Bureau of Investigation. J.P. Morgan's stock return was −23% in May 2012.

[20]Figure IA.1 in the Internet Appendix shows, in event time, cumulative equal-weighted hedge fund risk-adjusted return indexes for the clients of the affected prime brokers and those from a matched group of hedge funds.

5.2 Difference-in-difference regression

To formally assess whether clients of the affected prime brokers experience more pronounced impacts from a large adverse shock to their prime broker, we employ the following panel regression:

$$\begin{aligned}\hat{\alpha}_{i,t} = {} & b_1 \text{Lehman Event}_t \\ & + b_2 \text{Lehman Event}_t \times \text{Lehman Client}_i \\ & + b_3 \text{Lehman Event}_t \times \text{Lehman Unique Client}_i \\ & + b_4 \text{PB Events}_t + b_5 \text{PB Events}_t \times \text{PB Client}_i \\ & + b_6 \text{PB Events}_t \times \text{PB Unique Client}_i \\ & + c' X_{i,t-1} + a_i + \varepsilon_{i,t},\end{aligned} \tag{15}$$

where $\hat{\alpha}_{i,t}$ is the month t risk-adjusted returns for fund i. Specifically, $\hat{\alpha}_{i,t}$ is a constant plus residuals from an individual regression of hedge fund excess returns on the Fung and Hsieh (2004) seven factors.[21] Lehman Event$_t$ is an indicator variable equal to one during the event window surrounding the Lehman bankruptcy and zero otherwise. Lehman Client$_i$ is an indicator variable that is equal to one if a hedge fund was a client of Lehman two months prior to the bankruptcy. Lehman Unique Client$_i$ is equal to one if a hedge fund i used Lehman as their only prime broker at the time of its bankruptcy. PB Events$_t$, PB Client$_i$, and PB Unique Client$_i$ are indicator variables analogous to those defined for the Lehman event, but they apply to the Bear Stearns, UBS, and JP Morgan events. PB Events$_t$×PB Unique Client$_i$, Lehman Event$_t$×Lehman Client$_i$, PB Events$_t$×PB Client$_i$ and PB Events$_t \times$ PB Unique Client$_i$ are the interaction terms. A fund fixed effect is denoted by a_i, and $X_{i,t-1}$ is a vector of controls that includes the fund-specific, time-varying characteristics for each fund i (specifically, we consider past returns, size, and age). We use standard errors clustered by hedge fund and time. Our results are estimated on the

[21] We consider risk-adjusted returns for a more straightforward comparison across hedge funds of varying styles, however our findings remain consistent when simply using excess returns.

full Eurekahedge sample.[22]

We treat the Lehman event separately due to its extreme nature. The other three prime broker events are grouped together for enhanced statistical power and clarity of presentation. As discussed in the previous subsection, hedge funds can stop reporting after experiencing adverse shocks, hence we adjust their delisting returns. In the spirit of adjusting for equity delisting returns bias (Shumway, 1997), for each fund that stops reporting we add a delisting return of -30% for the month following the last reported return. We view this as a conservative adjustment as, particularly in the case of Lehman clients, such losses are well supported by anecdotal evidence (see, e.g., Aikman, 2010).[23] We consider a three-month event window (the month before, the event month, and the month after) as a benchmark specification, but also consider four and five month event windows. Our coefficients of interest, b_3 and b_6, on the interaction terms Lehman Event$_t \times$Lehman Unique Client$_i$ and PB Events$_t \times$PB Unique Client$_i$ capture the differential effects of the Lehman bankruptcy and the other three major prime broker shocks on their respective hedge fund clients that exclusively used the affected prime brokers. If large idiosyncratic shocks to a prime broker disproportionately and negatively affect the returns of its hedge fund clients, we would expect both coefficients to be negative and significant.

We report the results of regression (15) in Table 6. The coefficients on Lehman Event$_t$ and PB Events$_t$ capture the systematic effects (i.e., the average effect of these prime brokers shocks on hedge funds). These coefficients are large and negative in all specifications, however not statistically significant except for the coefficient on PB Events$_t$ that is marginally statistically significant in the last specification that considers a longer event window. The

[22]We also replicate our analysis using the matched sample of hedge funds, as referenced in Figure 4. The outcomes from this matched sample align closely with our baseline results, which we report in Internet Appendix Table IA.8.

[23]Using instead -10%, -50%, or -70% as a delisting return does not alter the general conclusion. There is little consensus in the literature on the appropriate delisting return adjustment. For example, Titman and Tiu (2010) use -100% , Ang and Bollen (2010) use -25%, and Sun and Teo (2019) use -10% as their delisting return base cases. Hodder, Jackwerth, and Kolokolova (2014) estimate an unconditional delisting return of -6%. However, they note that a large negative delisting return is possible under adverse circumstances, such as during the financial crisis.

economically large point estimates suggests that adverse financial sector shocks could impair average hedge fund performance, however weak statistical significance of these coefficients likely underscores cross-sectional differences. Specification I omits the indicator for the sole prime brokers. Hence, Lehman Event$_t$ × Lehman Client$_i$ and PB Events$_t$ × PB Client$_i$ capture the effect on all the funds that are connected to a particular affected prime broker, irrespective of whether it is a hedge fund's only prime broker or one of several. We find that the coefficients on Lehman Event$_t$ × Lehman Client$_i$ and PB Events$_t$ × PB Client$_i$ are both negative (-0.92 and -0.23, respectively) but only the coefficient on PB Events$_t$×PB Client$_i$ is statistically significant. The results of this specification suggest that, during the event window, the affected prime brokers' clients' risk-adjusted returns are worse than those of the other funds.

The lack of statistical significance for Lehman Event$_t$×Lehman Client$_i$ aligns with Figure 4, which indicates that primarily hedge funds using Lehman as their sole prime broker were adversely affected by its bankruptcy. This intuition is confirmed when we include the indicators Lehman Event$_t$×Lehman Unique Client$_i$ and PB Events$_t$×PB Unique Client$_i$ in specification II. Consistent with our hypothesis, the estimates of b_3 and b_6 are negative, -3.07% and -0.53% respectively, and both are statistically significant at the 1% level. In contrast, the estimates of b_2 and b_5, which, in this specification, only capture the effect of prime broker events on their hedge fund clients with multiple prime brokers, are no longer negative or statistically significant.[24] In other words, hedge funds exclusively using an affected prime broker faced significantly greater performance declines than other funds, whereas funds with multiple prime brokers remained largely unaffected by such shocks. Although the absolute size of the estimates decreases slightly, the results remain essentially unaltered with the inclusion of hedge fund controls in specification III.

[24]The estimates of b_2 on Lehman Event$_t$×Lehman Client$_i$ is positive and substantial, reaching statistical significance in specification III. This appears to be a consequence of the short event-window in our benchmark specification. The initial positive value observed is temporary; upon extending the event window, the positive point estimate diminishes, aligning more with our expectations.

Hedge funds with only one prime broker might be more sensitive to financial intermediary shocks, regardless of whether their specific prime broker is directly impacted. To rule out this potential effect driving our results, we introduce an additional indicator variable, One Broker$_i$, and its interactions with the relevant event indicators to regression (15). In line with our conjecture, we find that the estimates of Lehman Event$_t \times$ One Broker$_i$ and PB Events$_t \times$ One Broker$_i$ coefficients are both negative but statistically insignificant and economically small. However, we do observe a noticeable reduction in the point estimate of b_6 from -0.46 to -0.35. Nevertheless, the estimate of b_6 remains statistically significant at the 5% level. In contrast, the estimate of b_3 exhibits only a minor decrease from -2.96 to -2.68, highlighting the profound impact of the Lehman bankruptcy on its clients.

Lastly, specifications V and VI verify that the results are robust to different event windows. The magnitude and statistical significance of b_3 remain largely unchanged when expanding the event window from three to four or five months, suggesting that its economic significance actually increases with a longer event window. This pattern is also observed for b_6, with the economic significance also slightly increasing at longer event windows. These findings highlight that the adverse impact of prime broker shocks on their clients does not appear temporary, as we do not observe an obvious reversal. The average economic impact of the Lehman bankruptcy on clients who used it exclusively as their sole prime broker amounted to approximately a 10.80% (-2.16×5 months) loss in risk-adjusted return. Similarly, the average economic effect of the other three adverse prime broker shocks on their specific exclusive clients amounted to a 1.50% (-0.30×5 months) loss. Although notably smaller, this is still an economically meaningful effect.

In sum, the analysis of prime broker events shows that large individual prime broker shocks affect the performance of hedge fund clients who use the affected broker as their sole prime broker, with the impact being especially pronounced in the case of the Lehman bankruptcy. An important implication of this result is that the propagation of large (even extreme) negative individual prime broker shocks to their clients represents diversifiable

counterparty risk that is mitigated by using multiple prime brokers. This observation aligns with the conjecture by Dai and Sundaresan (2009) that hedge funds establish relations with several prime brokers for improved risk management. Indeed, this trend is evident post Lehman bankruptcy. Figure 1 depicts the increasing fraction of funds with multiple prime brokers over time (while only about 10% of hedge funds had multiple prime brokers in 2006, by 2021, around 45% reported multiple prime broker affiliations). However, using multiple prime brokers is not without cost, as it adds operational complexity and increases operational risk (see, also, Bittner and Jank, 2025, for a discussion). For instance, employing multiple prime brokers necessitates the duplication of various processes and complicates tasks such as netting collateral requirements across trades. Furthermore, prime brokers may offer incentives for exclusive relationships, such as favorable IPO allocations (see, e.g., Yang et al., 2021). Therefore, while the notable rise in hedge funds employing multiple prime brokers suggests an improved understanding of counterparty risk and a desire to diversify, it is unlikely that this practice will reach universal adoption.

6 Conclusion

Our paper provides comprehensive evidence of the significant impact that prime brokers have on hedge fund performance. We find that the average hedge fund's exposure to systematic financial intermediary risk exceeds what their holdings would suggest. This additional risk exposure is notably asymmetric, appearing only during adverse systematic FI shocks. In contrast, mutual funds do not show similar effects, underscoring the unique vulnerability of hedge funds to systematic prime broker shocks. These findings align with the concept of the prime broker shock propagation channel, where hedge funds may be forced to adjust their positions through leverage modifications during periods of prime broker distress, thereby passing prime broker shocks onto the hedge funds. Furthermore, we show that hedge funds suffer from large, negative shocks to their individual prime

brokers, but this impact is predominantly confined to funds that are exclusively reliant on the affected broker. This indicates that the risks associated with idiosyncratic prime broker shocks are, in fact, diversifiable.

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Table 1: Hedge fund summary statistics

The table presents summary statistics for hedge funds from the union database (BarclayHedge, CISD/Morningstar, Eurekahedge, HFR, and Lipper/TASS), and for hedge funds from the Eurekahedge database that report prime broker affiliations. N_{Funds} and N_{Mgrs} represent the total number of unique hedge funds and management companies, respectively. μ_{TS} and σ_{TS} are cross-sectional averages of each fund's average monthly excess returns and each fund's standard deviation of its monthly excess returns. σ_{XS} is the time-series average of monthly cross-sectional standard deviation of excess returns. μ_{TS}, σ_{TS}, and σ_{XS} are expressed in % and are annualized. The AUM statistics are time-series averages of monthly cross-sectional statistics (USD million), reflecting a typical distribution of hedge fund sizes available in a specific month within the sample. The sample period runs from January 2000 to June 2021.

	N_{Funds}	N_{Mgrs}	μ_{TS}	σ_{TS}	σ_{XS}	AUM_{Mean}	AUM_{Q25}	AUM_{Q50}	AUM_{Q75}
Full sample	16,160	7,103	5.06	15.04	10.91	348	12	47	181
Eurekahedge	5,397	3,046	5.92	15.06	8.82	219	14	50	178

Table 2: Top prime brokers over time

The table presents the market share of leading prime brokers based on hedge funds that report their prime broker affiliation and AUM to Eurekahedge (captured in snapshots from 2008, 2010, 2014, 2017, and 2021). Prime brokers are ranked by their hedge fund clients' total AUM. Market share percentages for the top 10 prime brokers are shown in parentheses next to their names. The table also reports the market shares (in %) of the top 10 and top 20 prime brokers, and the market share of prime brokers that are Fed Primary Dealers (Fed PD). Abbreviations are as follows: BAML: Bank of America Merrill Lynch, BNP P: BNP Paribas, BS: Bear Stearns, CS: Credit Suisse, DB: Deutsche Bank, GS: Goldman Sachs, IB: Interactive Brokers, JPM: J.P. Morgan, LB: Lehman Brothers, MF G: MF Global, ML: Merrill Lynch, MS: Morgan Stanley, and SocGen: Societe Generale.

	2008	2010	2014	2017	2021
1	MS (22.1)	MS (18.0)	GS (15.9)	GS (19.3)	MS (12.9)
2	GS (18.8)	GS (15.3)	CS (12.9)	MS (13.6)	GS (11.5)
3	BS (13.1)	JPM (14.3)	MS (10.4)	CS (11.9)	Barclays (10.3)
4	DB (8.4)	UBS (10.8)	UBS (10.3)	JPM (10.5)	UBS (9.7)
5	UBS (8.0)	CS (8.4)	JPM (10.1)	UBS (8.1)	JPM (9.3)
6	ML (3.6)	DB (6.5)	BAML (6.9)	DB (7.1)	BAML (6.5)
7	CS (3.6)	SocGen (4.5)	DB (6.0)	BAML (5.9)	CS (5.5)
8	LB (3.0)	BAML (3.7)	Citi (5.5)	Barclays (4.2)	DB (4.3)
9	SocGen (3.0)	Citi (3.1)	Barclays (5.1)	SocGen (3.5)	SocGen (4.0)
10	Citi (2.6)	BNP P (2.6)	SocGen (3.2)	Citi (3.3)	SEB (3.3)
Top 10	86.2	87.3	86.2	87.3	77.4
Top 20	94.8	94.9	95.2	95.8	91.2
Fed PD	88.3	86.5	91.7	92.4	83.6

Table 3: Hedge fund and mutual fund holdings data

This table presents cross-sectional summary statistics (mean, standard deviation, Q25, Q50 and Q75) of the sample of hedge funds (Panel A) and mutual funds (Panel B) described in Section 3. The first row reports statistics on the number of time-series observations per fund. The next four rows report the statistics of the time-series medians of fund AUM (in USD billion), the ratio of holdings market value to reported AUM (TNA Ratio), the number of stocks held and the quarterly turnover (the minimum of dollar value of buys and sales divided by the average AUM across the two adjacent quarters). Market and FI betas are the coefficients from regressing monthly reported/holdings-implied excess returns on the market and the FI factor. Similarly, HML betas are derived from regressing monthly reported/holdings-implied excess returns on the market and the Fama and French (1993) HML factor. The sample period runs from January 2000 to June 2021.

Panel A: Hedge funds

Statistic	Mean	Std.Dev.	Q25	Q50	Q75
Number of TS observations	90.351	57.316	42.000	75.000	126.000
AUM	0.409	0.478	0.106	0.216	0.478
TNA ratio	1.406	1.062	0.684	1.005	1.834
Number of holdings	73.889	88.051	22.000	40.000	81.000
Turnover	0.218	0.125	0.110	0.198	0.318
Beta Market					
Reported	0.475	0.377	0.158	0.429	0.726
Holdings-implied	1.122	0.327	0.905	1.097	1.300
Beta FI					
Reported	0.023	0.140	−0.064	0.018	0.108
Holdings-implied	0.016	0.176	−0.090	0.009	0.103
Beta HML					
Reported	−0.006	0.291	−0.157	0.001	0.158
Holdings-implied	0.019	0.353	−0.207	0.010	0.252

Panel B: Mutual funds

Statistic	Mean	Std.Dev.	Q25	Q50	Q75
Number of TS observations	82.177	37.198	45.000	86.000	116.750
AUM	0.984	1.713	0.050	0.206	0.978
TNA ratio	0.936	0.075	0.922	0.959	0.983
Number of holdings	90.057	79.686	41.000	60.500	100.500
Turnover	0.107	0.068	0.055	0.091	0.141
Beta Market					
Reported	0.958	0.177	0.840	0.962	1.087
Holdings-implied	1.004	0.162	0.878	0.995	1.121
Beta FI					
Reported	0.010	0.105	−0.068	0.004	0.085
Holdings-implied	0.013	0.110	−0.069	0.006	0.089
Beta HML					
Reported	0.003	0.247	−0.184	0.020	0.197
Holdings-implied	0.015	0.261	−0.184	0.026	0.216

Table 4: Prime broker channel

This table presents the results from a test for excess systematic financial intermediary risk exposure, $\beta^{\text{PBCh.}}$, described in Section 2.1. Panel A presents the main specification considering a two-factor model comprised of market and FI factors, while Panel B presents the placebo specification considering a two-factor model of market and Fama and French (1993) HML factors. $\widehat{a}$ is the intercept and is $\widehat{b}$ the slope coefficient from a cross-sectional regression of factor betas estimated from reported returns on the factor betas estimated from the holdings-based returns. Downside factor betas, β_{down}, are estimated using the months with negative factor returns, and upside betas, β_{up}, are estimated using the months with positive factor returns. White (1980) standard errors are reported in parentheses. a_{model} is the regression intercept implied by the parameterized model of fund returns (see equation (12) and Subsection 4 for discussion on parameter choice). $\widehat{\beta}^{\text{PBCh.}}$ is the estimate of the prime broker channel beta, calculated as the difference between $\widehat{a}$ and a_{model}. The p-value of a one-sided test is reported in brackets. The last two columns report measures of the economic effect of the estimates. $\widehat{\beta}^{\text{PBCh.}}/\sigma(\beta_{Hlds})$ is $\widehat{\beta}^{\text{PBCh.}}$ divided by the standard deviation of corresponding holdings betas. $\widehat{\beta}^{\text{PBCh.}} \times 2\sigma_{Factor}$ is the influence of a 2-standard-deviation monthly shock in the factor of interest (FI or HML) on the fund universe of interest (hedge funds or mutual funds). In the case of up- (down-)side betas, we use the corresponding semi-variance to calculate the value of a 2-standard-deviation factor shock.

	$\widehat{a}$	$\widehat{b}$	R^2	N	a_{model}	$\widehat{\beta}^{\text{PBCh.}}$	$\frac{\widehat{\beta}^{\text{PBCh.}}}{\sigma(\beta_{Hlds})}$	$\widehat{\beta}^{\text{PBCh.}} \times 2\sigma_{Factor}$
Panel A: Financial intermediary factor								
Hedge funds								
β^{FI}	0.023	0.547	0.385	523	0.002	0.020	11.62%	27 bps
	(0.005)	(0.052)				[0.000]		
β^{FI}_{down}	0.083	0.512	0.272	357	0.018	0.065	27.68%	62 bps
	(0.014)	(0.068)				[0.000]		
β^{FI}_{up}	−0.003	0.574	0.360	382	0.011	−0.015	−6.50%	-12 bps
	(0.008)	(0.062)				[0.961]		
Mutual funds								
β^{FI}	−0.001	0.926	0.936	1,834	0.001	−0.003	−2.27%	-3 bps
	(0.001)	(0.007)				[1.000]		
β^{FI}_{down}	0.007	0.929	0.888	1,251	0.008	−0.001	−0.45%	-1 bps
	(0.002)	(0.012)				[0.629]		
β^{FI}_{up}	−0.003	0.945	0.945	1,410	0.001	−0.004	−2.22%	-3 bps
	(0.001)	(0.008)				[1.000]		
Panel B: HML (placebo)								
Hedge funds								
β^{HML}	0.004	0.513	0.383	523	0.003	0.001	0.17%	0 bps
	(0.010)	(0.039)				[0.477]		
β^{HML}_{down}	0.031	0.536	0.366	389	0.009	0.021	4.51%	10 bps
	(0.017)	(0.050)				[0.111]		
β^{HML}_{up}	0.014	0.506	0.366	338	0.010	0.005	1.15%	2 bps
	(0.015)	(0.048)				[0.381]		
Mutual funds								
β^{HML}	−0.008	0.944	0.971	1,834	0.002	−0.010	−3.75%	-7 bps
	(0.001)	(0.005)				[1.000]		
β^{HML}_{down}	0.001	0.922	0.933	1,499	0.008	−0.007	−2.26%	-3 bps
	(0.002)	(0.016)				[0.999]		
β^{HML}_{up}	−0.010	0.947	0.959	1,189	0.002	−0.012	−4.06%	-6 bps
	(0.002)	(0.008)				[1.000]		

Table 5: Prime broker channel (alternative null models)

This table presents the results from a test for excess systematic financial intermediary risk exposure, $\beta^{\text{PBCh.}}$, described in Section 2.1, controlling for alternative factor models. The table is similar to Table 4, with the only difference being that the factor models differ. Panel A presents the specification considering the Fama-French five factor model and FI. Panel B presents the a model comprised of MKT, Pastor and Stambaugh Illiquity factor, and FI. Panel C presents the a model comprised of MKT, changes in the TED spread, and FI. Panel D uses MKT and FI and controls for the return(s) of each manager's individual prime broker(s). See Table 4 for a full description. See Internet Appendix Table IA.6 for results for mutual funds.

	$\widehat{a}$	$\widehat{b}$	R^2	N	a_{model}	$\widehat{\beta}^{\text{PBCh.}}$	$\frac{\widehat{\beta}^{\text{PBCh.}}}{\sigma(\beta_{Hlds})}$	$\widehat{\beta}^{\text{PBCh.}} \times 2\sigma_{Factor}$
Panel A: Fama French five factors, and FI								
Hedge Funds								
β^{FI}	0.033	0.441	0.205	523	0.002	0.031	21.71%	42 bps
	(0.005)	(0.064)				[0.000]		
β^{FI}_{down}	0.068	0.463	0.192	357	0.014	0.054	26.01%	51 bps
	(0.013)	(0.105)				[0.000]		
β^{FI}_{up}	0.014	0.513	0.260	382	0.006	0.008	4.11%	6 bps
	(0.009)	(0.073)				[0.188]		
Panel B: MKT, Pastor & Stambaugh illiquidity, and FI								
Hedge funds								
β^{FI}	0.033	0.529	0.356	523	0.004	0.029	16.88%	39 bps
	(0.006)	(0.055)				[0.000]		
β^{FI}_{down}	0.067	0.490	0.242	357	0.013	0.054	23.06%	52 bps
	(0.013)	(0.072)				[0.000]		
β^{FI}_{up}	0.009	0.601	0.358	382	0.018	−0.009	−4.15%	-8 bps
	(0.010)	(0.082)				[0.818]		
Panel C: MKT, ΔTED, and FI								
Hedge funds								
β^{FI}	0.029	0.541	0.383	523	0.004	0.026	14.85%	34 bps
	(0.006)	(0.052)				[0.000]		
β^{FI}_{down}	0.072	0.508	0.280	357	0.016	0.056	24.79%	53 bps
	(0.013)	(0.065)				[0.000]		
β^{FI}_{up}	0.005	0.578	0.376	382	0.013	−0.007	−3.13%	-6 bps
	(0.008)	(0.054)				[0.812]		
Panel D: MKT, individual prime broker excess return, and FI								
Hedge Funds								
β^{FI}	0.024	0.503	0.361	252	0.005	0.020	10.55%	26 bps
	(0.008)	(0.051)				[0.004]		
β^{FI}_{down}	0.081	0.413	0.196	178	0.018	0.063	23.38%	61 bps
	(0.017)	(0.083)				[0.000]		
β^{FI}_{up}	−0.008	0.572	0.379	190	0.011	−0.019	−7.76%	-16 bps
	(0.012)	(0.070)				[0.941]		

Table 6: Event studies

This table presents panel regressions of monthly hedge fund risk-adjusted returns (in %) on various indicator variables and their interactions. The risk-adjusted returns equal the constant plus the residuals from individual regressions of hedge fund excess returns on the Fung and Hsieh (2004) seven factors. Lehman Event is an indicator variable equal to one during the event window around the Lehman bankruptcy (September 2008) and zero otherwise. Lehman Client is an indicator variable that is equal to one if a hedge fund was a Lehman client during the bankruptcy event. PB Events is an indicator variable that is equal to one during the prime broker event window. The three prime broker events considered are the failure of Bear Stearns (March 2008), the trading loss scandal of UBS (September 2011), and the trading loss scandal of JP Morgan (April 2012). PB Client is an indicator variable that is equal to one if a hedge fund was a client of the affected prime broker during its respective event. Lehman Unique Client and PB Unique Client are indicator variables equal to one if a hedge fund uses one of the affected prime brokers as the sole prime broker during the event window. One Broker is an indicator variable equal to one if a hedge fund is affiliated with only a single prime broker. In specifications I−IV, the event window is three months: the month before, the event month, and the month after (referred to as 1 & 1). Specifications V and VI consider a four month (1 & 2) and five month (1 & 3) event window, respectively. Hedge fund fixed effects are included in all specifications. Controls include lagged hedge fund AUM, age, and return. Standard errors in parentheses are clustered by fund and time. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively. The sample period runs from January 2000 to June 2021.

	I	II	III	IV	V	VI
Lehman Event	−1.842	−1.842	−1.838	−1.600	−1.032	−0.952
	(1.326)	(1.326)	(1.340)	(1.089)	(0.955)	(0.769)
Lehman Event × Lehman Client	−0.921	0.760	0.845**	0.610	−0.066	0.197
	(0.675)	(0.471)	(0.397)	(0.419)	(0.606)	(0.530)
Lehman Event × Lehman Unique Client		−3.067***	−2.958***	−2.681***	−2.653***	−2.160***
		(0.797)	(0.670)	(0.614)	(0.614)	(0.774)
Lehman Event × One Broker				−0.282	−0.177	−0.070
				(0.320)	(0.260)	(0.230)
PB Events	−0.708	−0.708	−0.709	−0.588	−0.506	−0.508*
	(0.610)	(0.610)	(0.601)	(0.394)	(0.317)	(0.259)
PB Events × PB Client	−0.230***	0.122	0.185	0.092	0.094	0.090
	(0.086)	(0.128)	(0.156)	(0.139)	(0.124)	(0.117)
PB Events × PB Unique Client		−0.533***	−0.463**	−0.348**	−0.274*	−0.300**
		(0.199)	(0.195)	(0.153)	(0.141)	(0.142)
PB Events × One Broker				−0.149	−0.125	−0.020
				(0.308)	(0.251)	(0.219)
Observations	561,841	561,841	556,444	556,444	556,444	556,444
Adjusted R^2	0.017	0.017	0.029	0.029	0.028	0.028
Hedge fund fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	No	Yes	Yes	Yes	Yes
Event window	1 & 1	1 & 1	1 & 1	1 & 1	1 & 2	1 & 3

Figure 1: Hedge funds with multiple prime brokers

The figure shows the temporal evolution of the proportion of hedge funds using multiple prime brokers, based on semi-annual snapshots from the Eurekahedge database, spanning from June 2006 to January 2021.

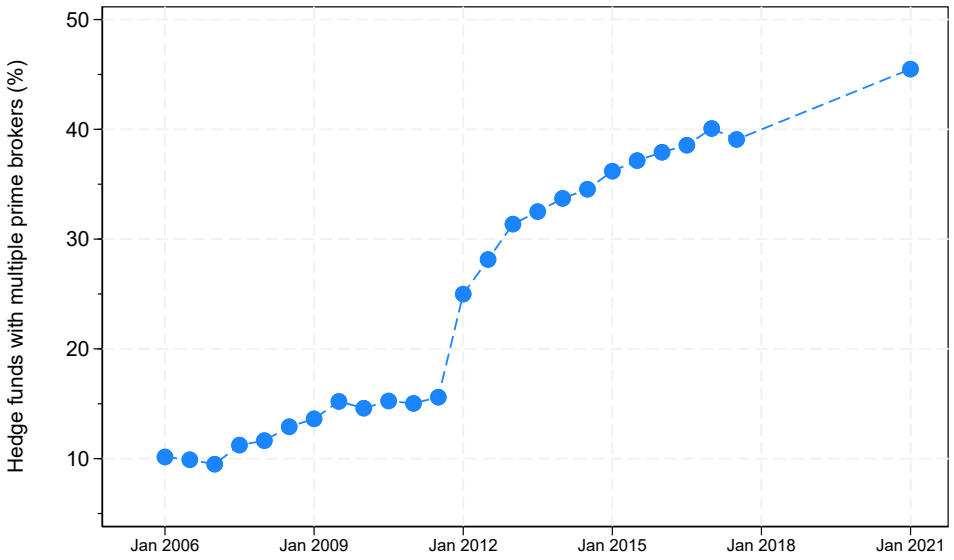
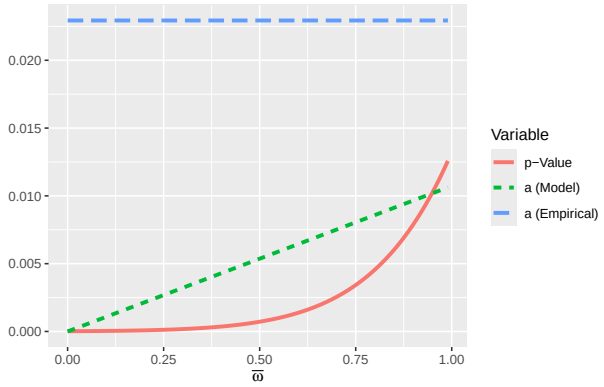


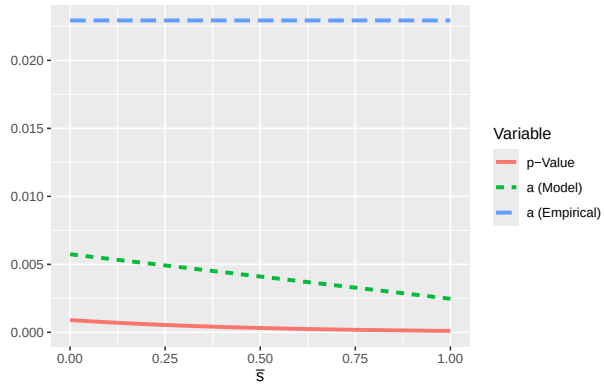
Figure 2: Parameter sensitivity analysis w.r.t. $\bar{\omega}$ and $\bar{s}$

The figure presents the results of a sensitivity analysis on the parameters $\bar{\omega}$ (the average share invested in unobserved positions) and $\bar{s}$ (the average proportion of a long position's beta hedged with short positions). The empirically estimated intercept from equation (12) is depicted as the dashed blue line. The dotted green line represents the model-implied intercept following equation (12), varying $\bar{\omega}$ in Panels A and C, and $\bar{s}$ in Panels B and D. The p–value of testing whether $\bar{\beta}^{\text{PBCh.}}$ is greater than 0 is plotted as the solid red line. Panels A and B focus on systematic financial intermediary β's estimated on all observations. Panels C and D focus on systematic financial intermediary downside β's, i.e., β's estimated on observations where $f_t^{FI} < 0$.

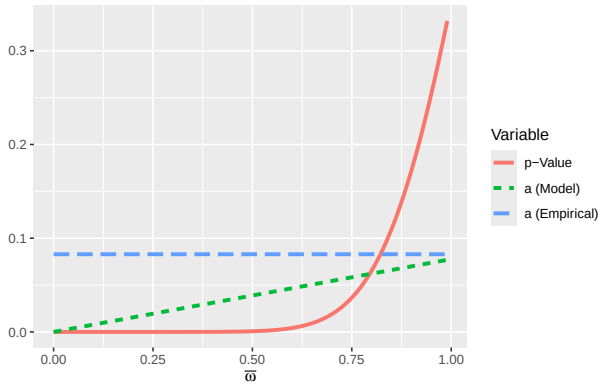
Panel A: Beta sensitivity w.r.t. $\bar{\omega}$



Panel B: Beta sensitivity w.r.t. $\bar{s}$



Panel C: Downside beta sensitivity w.r.t. $\bar{\omega}$



Panel D: Downside beta sensitivity w.r.t. $\bar{s}$

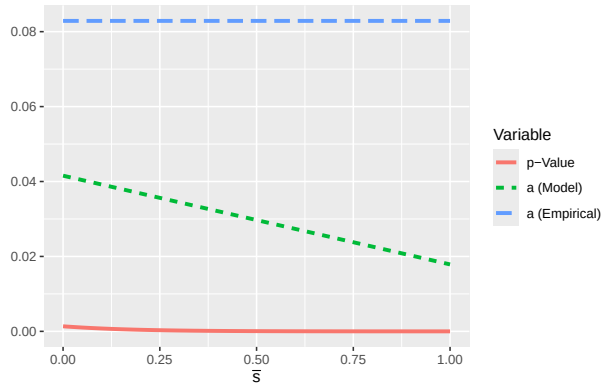
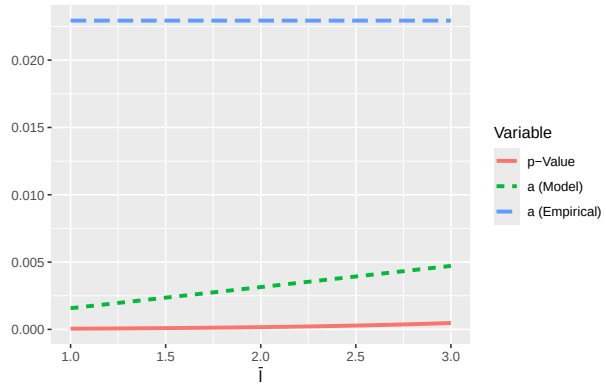


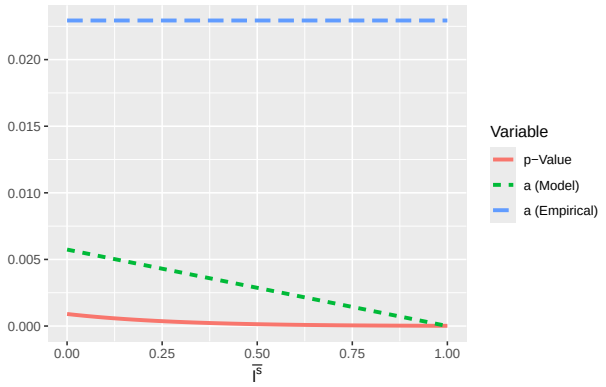
Figure 3: Parameter sensitivity analysis w.r.t. $\bar{\ell}$ and $\bar{\ell}^s$

The figure presents the results of a sensitivity analysis on the parameters $\bar{\ell}$ (average leverage) and $\bar{\ell}^s$ (average short exposure). The empirically estimated intercept from equation (12) is depicted as the dashed blue line. The dotted green line represents the model-implied intercept following equation (12), varying $\bar{\ell}$ in Panels A and C, and $\bar{\ell}^s$ in Panels B and D. The p–value of testing whether $\bar{\beta}^{\text{PBCh.}}$ is greater than 0 is plotted as the solid red line. Panels A and B focus on systematic financial intermediary β's estimated on all observations. Panels C and D focus on systematic financial intermediary downside β's, i.e., β's estimated on observations where $f_t^{FI} < 0$.

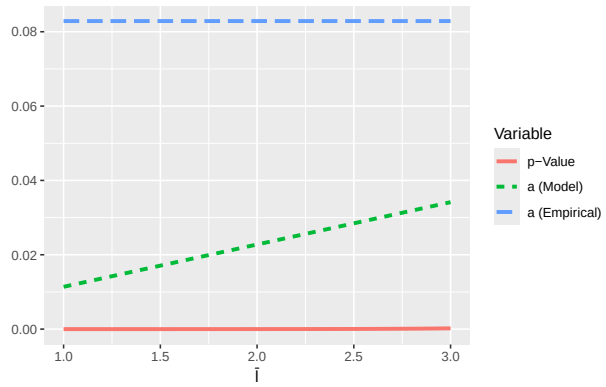
Panel A: Beta sensitivity w.r.t. $\bar{\ell}$



Panel B: Beta sensitivity w.r.t. $\bar{\ell}^s$



Panel C: Downside beta sensitivity w.r.t. $\bar{\ell}$



Panel D: Downside beta sensitivity w.r.t. $\bar{\ell}^s$

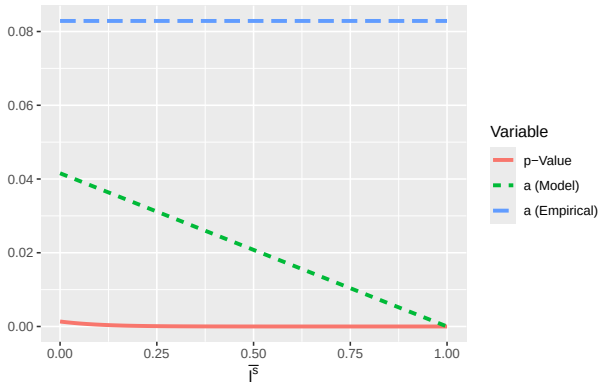
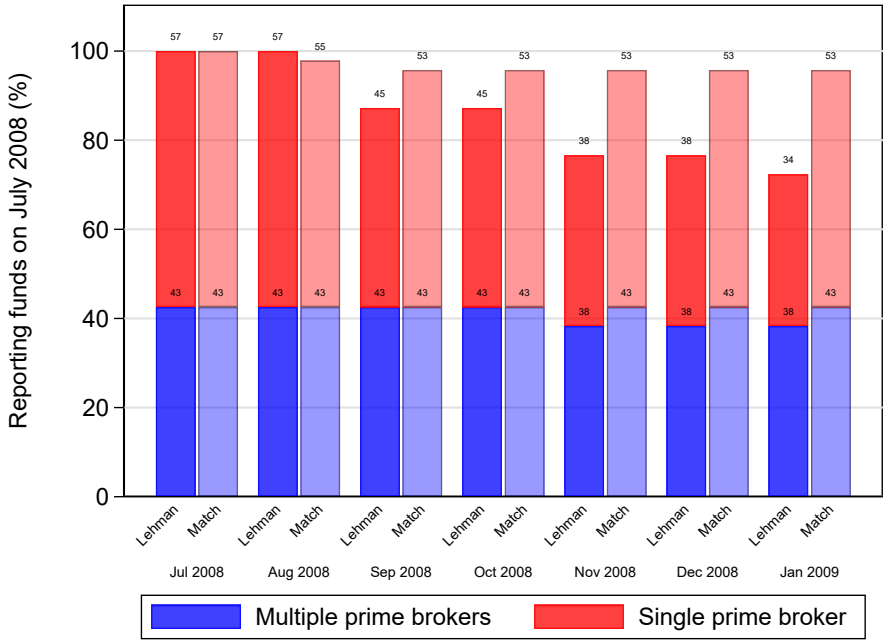


Figure 4: Event study of Lehman bankruptcy

The figure presents the proportion of Lehman's hedge fund clients that reported returns to the Eurekahedge database in July 2008 and continued to do so between August 2008 and January 2009. Taking the number of reporting clients in July 2008 as 100%, the figure illustrates how many of them also reported to the database in the subsequent months. The figure also shows reporting proportions for a matched group of hedge funds using a different prime broker. Hedge funds are matched based on the number of prime brokers, style, AUM, and past returns. The figure differentiates between hedge funds with multiple prime brokers (blue shades) and those with only one prime broker (red shades).



Appendix

A The effect of correlation between observed and unobserved positions

We assume the correlation between $\widehat{\beta}_i^{\mathrm{U}}$ and $\widehat{\beta}_i^{\mathrm{O}}$ to be zero. Below, we explore the effects of assuming a non-zero correlation/covariance.

$$\widehat{b} = \bar{\ell}(1-\bar{\omega}) - \bar{\ell}\ell_i^S\bar{s}(1-\bar{\omega}) + \bar{\ell}\bar{\omega}(1-\bar{\ell}^S\bar{s})\frac{\mathrm{Cov}\left(\widehat{\beta}_i^{\mathrm{U}}, \widehat{\beta}_i^{\mathrm{O}}\right)}{\mathrm{Var}\left(\widehat{\beta}_i^{\mathrm{O}}\right)}. \tag{A.1}$$

$$\begin{aligned}
\widehat{a} &= \bar{\beta} - \widehat{b} \times \bar{\beta}^O \\
&= \bar{\ell}(1-\bar{\omega})\bar{\beta}^{\mathrm{O}} + \bar{\ell}\bar{\omega}\bar{\beta}^{\mathrm{U}} \\
&- \bar{\ell}\bar{\ell}^S\bar{\beta}^{\mathrm{S}} + \bar{\beta}^{\mathrm{PBCh.}} - \left[\bar{\ell}(1-\bar{\omega}) - \bar{\ell}\ell_i^S\bar{s}(1-\bar{\omega}) + \bar{\ell}\bar{\omega}(1-\bar{\ell}^S\bar{s})\frac{\mathrm{Cov}\left(\widehat{\beta}_i^{\mathrm{U}}, \widehat{\beta}_i^{\mathrm{O}}\right)}{\mathrm{Var}\left(\widehat{\beta}_i^{\mathrm{O}}\right)}\right] \times \bar{\beta}^O \\
&= \bar{\ell}\bar{\omega}\bar{\beta}^{\mathrm{U}} - \bar{\ell}\bar{\ell}^S\bar{s}((1-\bar{\omega})\bar{\beta}^{\mathrm{O}} + \bar{\omega}\bar{\beta}^{\mathrm{U}}) + \bar{\beta}^{\mathrm{PBCh.}} + \bar{\ell}\bar{\ell}^S\bar{s}(1-\bar{\omega})\bar{\beta}^O - \bar{\ell}\bar{\omega}(1-\bar{\ell}^S\bar{s})\frac{\mathrm{Cov}\left(\widehat{\beta}_i^{\mathrm{U}}, \widehat{\beta}_i^{\mathrm{O}}\right)}{\mathrm{Var}\left(\widehat{\beta}_i^{\mathrm{O}}\right)} \times \bar{\beta}^O \\
&= \left(1-\bar{\ell}^S\bar{s}\right)\bar{\ell}\bar{\omega}\bar{\beta}^U + \bar{\beta}^{\mathrm{PBCh.}} - \bar{\ell}\bar{\omega}(1-\bar{\ell}^S\bar{s})\frac{\mathrm{Cov}\left(\widehat{\beta}_i^{\mathrm{U}}, \widehat{\beta}_i^{\mathrm{O}}\right)}{\mathrm{Var}\left(\widehat{\beta}_i^{\mathrm{O}}\right)} \times \bar{\beta}^O.
\end{aligned} \tag{A.2}$$

As evident from the final equation, a positive correlation between $\widehat{\beta}_i^{\mathrm{U}}$ and $\widehat{\beta}_i^{\mathrm{O}}$ will reduce the model-implied estimate of a. This, in turn, lowers the threshold for $\widehat{\beta}^{\mathrm{PBCh.}}$ to exceed 0. Conversely, a negative correlation would have the opposite effect. However, justifying such a negative correlation between FI-betas of observed and unobserved positions ex-ante is challenging.

Internet Appendix

How exposed are hedge funds to prime broker risk?

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IA.A Creating a union database of hedge fund managers

Step 0: Basic filters

Separately, for each of the five hedge fund databases (BarclayHedge, CISD/Morningstar, Eurekahedge, HFR, and Lipper/TASS), we apply the following basic filters:

- Retain only the hedge funds that report net-of-fees returns.
- Exclude any funds-of-funds.
- Exclude funds that never report their currency, style, or AUM.
- Exclude any hedge funds that report consecutive identical returns for more than three months (e.g., June 2002: 2%, July 2002: 2%, August 2002: 2%) if such returns represent more than 5% of the total returns reported by that fund. See Almeida, Ardison, and Garcia (2020) for details.
- Exclude any hedge funds that report more than twice "blocks" of identical returns. Specifically, we consider blocks of two to twelve returns. For example, repeated blocks of two returns could look like this: June 2002: 2%, July 2002: 2.5%, August 2002: 2%, August 2002: 2.5%. See Almeida et al. (2020) for details.
- When a hedge fund has multiple share classes, we consider only a single share class for each fund (retaining the fund with the longest time series) and aggregate their AUMs.

Step 1: Name cleaning

We first standardize and clean manager names by applying the following procedure to the list of manager names of all hedge fund databases as well as the Thomson Reuters 13F database:

- Remove any non-UTF-8 character
- Make everything uppercase
- Remove unnecessary whitespaces
- Remove terms in parentheses (often the location, e.g., 'Cayman')
- Remove punctuation (e.g. ',' in front of LLC)
- Standardize use of & / 'and'
- Standardize acronyms to be spelled without whitespaces in between (e.g. 'AQR' instead of 'A Q R')
- Replace standard abbreviations (e.g. 'MGMT' with 'MANAGEMENT')
- Remove legal form (such as 'LLC')

- Remove region from the end of the name (such as 'Luxemburg')

Step 2: Identify duplicate managers within a database

Next, based on the standardized names, we identify all managers with the same standardized name. If the database uses manager IDs (Lipper/TASS and BarclayHedge), we replace the IDs of duplicates with the first ID within each group of duplicates. For the other databases (CISD, Eurekahedge, HFR), we assign numeric IDs based on the standardized name; that is, managers sharing the same standardized name receive the same ID. In the 13F database, different IDs (mgrno), even with identical standardized names, typically represent different filers. Hence, we keep them separate and will use additional characteristics to attempt merging with the other databases later.

Step 3: Initial name merge based on standardized names

We begin by merging manager names from BarclayHedge and Lipper/TASS. Subsequently, we merge these with the union of CISD, HFR, and Eurekahedge, in this order. For each name in database A, we loop through all names in database B, comparing them using the following procedure:

We rank matches in the following order (best to worst):

- The standardized names of A and B are exactly equal
- The standardized names of A and B contain multiple unique words (words that are not on the list of abbreviations, e.g. 'MANAGEMENT') and those are exactly equal. If there are multiple such cases, prefer the one where the Levenshtein distance between the two is smallest.
- The standardized names of A and B contain one unique word, that is exactly equal, and there is only one non-unique word missing in either A or B (e.g. 'XYZ CAPITAL MANAGEMENT' and 'XYZ CAPITAL') preventing a perfect match.
- The standardized names of A and B contain one unique word, that is exactly equal, and only one of the non-unique words from A and B is different (e.g. 'XYZ CAPITAL MANAGEMENT' and 'XYZ CAPITAL ADVISORS'). If there are multiple such cases, prefer the one where the Levenshtein distance between the two is smallest.
- The standardized names of A and B contain one unique word, that is exactly equal, and multiple of the non-unique words from A and B are different. If there are multiple such cases, prefer the one where the Levenshtein distance between the two is smallest.

We retain all perfect matches (as per the first bullet point) and other matches that are the best match for both A (from all possible matches in B) and vice versa. An example where this condition is not met: XYZ Capital' from B could be the best match for XYZ CAPITAL MANAGEMENT' in A. However, if A also contains an XYZ Capital', this would be the best match for XYZ Capital' from B. Consequently, XYZ CAPITAL MANAGEMENT' from A would not have a match in B. We assume that database A intentionally listed XYZ CAPITAL MANAGEMENT' and 'XYZ Capital' as separate managers.

Step 4: Identify duplicate funds using return correlations

We first merge fund returns from BarclayHedge and CISD, then generate the full correlation matrix for all funds. Any funds with a correlation of $\geq 99\%$ (based on either reported returns or returns converted to USD), and sharing an overlapping period of at least 12 months, are flagged as duplicates.

From these groups of potential duplicates, we retain the one with the longest history of returns and record the IDs of other members in the group. Next, using the resultant union database, we merge it with Eurekahedge, HFR, and Lipper/TASS, following the same procedure, in that order. Ultimately, this results in a consolidated database of fund IDs, each representing the same fund. This includes different share classes of the same fund within one database, as well as identical funds listed across multiple databases.

Step 5: Manually overwrite manager names, using information from the correlation exercise

From the correlation analysis, we compile a list of managers with funds showing 99% correlation but recorded as different entities. We manually review this list to determine if any of these managers are, in fact, the same. For instance, discrepancies may arise when one database uses an older name for a manager, while another uses a more recent name following any name changes. This process also helps us identify several typos that hindered matching in the initial iteration

Step 6: Repeat name matching procedure, using correlation as tie-breaker

We repeat the matching procedure from step 3, but include the manual fixes from step 5. Also, we additionally use the maximum correlation between any two funds of two managers as an additional tie-breaker, in case of multiple valid name matches.

Step 7: Match names with 13F

Lastly, we apply the same name matching techniques to align the union database of hedge fund managers with the 13F database. For all matches meeting any of the criteria outlined in step 3, we use several tie-breakers: the median absolute value of the logarithm of the ratio of holdings market value to reported fund AUM (rounded to whole numbers) serves as the primary tie-breaker. The secondary tie-breaker is the number of overlapping monthly observations between manager returns and 13F database returns, rounded to the nearest hundred. Finally, the quality of the name match, as measured by the Levenshtein distance, is used as the last tie-breaker.

Main sample of hedge fund managers

To be included in our main sample of hedge fund managers, a number of criteria must be met:

- Manager with $\leq$5 funds
- each of these up to 5 funds are 'eligible' (equity-related style, some North America exposure — specifics below)

  - Hedge fund (not fund of fund, CTA or MAF)
  - Kosowski Style $\in$ (Sector, Long/Short, Long Only, Market-Neutral, Multi-Strategy, Event Driven)
  - Main style cannot contain ("debt", "bond", "etfs", "europe", "EUR", "real estate")
  - Sub-style cannot contain ("fixed", "multi", "currency", "debt", "bond", "credit", "emerging", "commodities", "option", "volatility", "mortgage", "etfs", "macro", "insurance")
  - If we have non-missing exposure to North America, it cannot be 0
  - If we have non-missing geographical focus, it must be $\in$ (N. America, North America, Global)
  - If we have non-missing focus-us and focus north-america, one of them has to be =1
  - If we have one of focus-us and focus north-america non-missing, it has to be =1
  - If we have non-missing focus-other, it must be =0, unless we also have neither focus-us=1 or focus north-america=1
  - If we have non-missing ae-equities, it cannot be =0

- 13F must classify the manager as typecode (3=investment companies and their managers, 4=independent investment advisor, 5=all others) at least once (so they cannot only be classified as (1=bank, 2=insurance company))
- At least 24 monthly observations
- Median (over life of manager) of $|log(TNAratio)| < log(5)$
  - TNA-Ratio = $\frac{aum13f}{aumMgr}$
  - We measure the TNA ratio once with aumMgr and once with aumMgrMax (which is the maximum AUM you get, when you always use the largest aums for a particular fund, when there are alternative numbers from different databases)
  - only one of these TNA ratios (either the aumMgr-based or the aumMgrMax-based) has to satisfy the constraint

Full sample of 13F filers

As a robustness check, we work with a larger sample that, in addition to the managers selected above, includes managers with less strict criteria:

- Manager with >5 but $\leq$10 funds or manager with $\leq$5 funds, some or all of which are not 'eligible' (as defined above)

- 13F must classify the manager as typecode (3=investment companies and their managers, 4=independent investment advisor, 5=all others) at least once (so they cannot only be classified as (1=bank, 2=insurance company))
- At least 24 monthly observations
- No other restrictions (in particular, no TNA-ratio criterion and no 'eligibility' check)

Table IA.1: Systematic prime-broker relationship channel (all 13F hedge fund matches)

This table presents the results from a test for excess financial intermediary risk exposure described in subsection 2.2 of the main paper. For details see caption to Table 4 in the paper.
The difference here is that we use a larger, less strictly selected sample of hedge fund managers, as described in Section IA.A of the Internet Appendix.

	$\widehat{a}$	$\widehat{b}$	R^2	N	a_{model}	$\widehat{\beta}^{\text{PBCh.}}$	$\frac{\widehat{\beta}^{\text{PBCh.}}}{\sigma(\beta_{Hlds})}$	$\widehat{\beta}^{\text{PBCh.}} \times 2\sigma_{Factor}$
Hedge Funds								
β^{FI}	0.021	0.340	0.181	1,305	0.004	0.017	10.34%	22 bps
	(0.004)	(0.043)				[0.000]		
β^{FI}_{down}	0.081	0.384	0.140	923	0.022	0.059	26.42%	57 bps
	(0.009)	(0.045)				[0.000]		
β^{FI}_{up}	0.007	0.291	0.129	992	0.015	−0.008	−3.89%	-7 bps
	(0.006)	(0.048)				[0.913]		

Table IA.2: Prime broker channel (prime broker factor)

This table presents the results from a test for excess financial intermediary risk exposure described in subsection 2.2 of the main paper. For details see caption to Table 4 in the paper.
The difference here is that we use an alternative FI factor, defined as the excess return to an equal-weighted (Panel A) or hedge-fund-AUM-weighted (Panel B) portfolio of listed prime brokers in our sample.

	$\widehat{a}$	$\widehat{b}$	R^2	N	a_{model}	$\widehat{\beta}^{\text{PBCh.}}$	$\frac{\widehat{\beta}^{\text{PBCh.}}}{\sigma(\beta_{Hlds})}$	$\widehat{\beta}^{\text{PBCh.}} \times 2\sigma_{Factor}$
Panel A: Equal-weighted prime broker factor								
Hedge Funds								
β^{PBF}	0.038	0.533	0.376	523	0.006	0.032	16.20%	45 bps
	(0.007)	(0.051)				[0.000]		
β^{PBF}_{down}	0.077	0.426	0.236	334	0.014	0.062	23.34%	60 bps
	(0.012)	(0.050)				[0.000]		
β^{PBF}_{up}	0.021	0.560	0.370	409	0.012	0.010	4.01%	9 bps
	(0.010)	(0.055)				[0.168]		
Mutual Funds								
β^{PBF}	0.002	0.934	0.940	1,834	0.003	−0.001	−0.90%	-2 bps
	(0.001)	(0.007)				[0.947]		
β^{PBF}_{down}	0.008	0.914	0.891	1,223	0.006	0.002	1.44%	2 bps
	(0.002)	(0.014)				[0.149]		
β^{PBF}_{up}	−0.001	0.946	0.943	1,437	0.002	−0.003	−2.03%	-3 bps
	(0.001)	(0.008)				[0.999]		
Panel B: Hedge-fund-AUM-weighted prime broker factor								
Hedge Funds								
β^{PBF}	0.024	0.497	0.335	523	0.006	0.018	14.41%	31 bps
	(0.004)	(0.043)				[0.000]		
β^{PBF}_{down}	0.067	0.459	0.245	342	0.009	0.058	34.50%	63 bps
	(0.008)	(0.059)				[0.000]		
β^{PBF}_{up}	0.004	0.503	0.326	395	0.010	−0.006	−3.15%	-6 bps
	(0.007)	(0.046)				[0.812]		
Mutual Funds								
β^{PBF}	0.001	0.933	0.941	1,834	0.001	−0.000	−0.28%	-0 bps
	(0.001)	(0.007)				[0.685]		
β^{PBF}_{down}	0.012	0.922	0.894	1,278	0.004	0.007	7.74%	8 bps
	(0.001)	(0.015)				[0.000]		
β^{PBF}_{up}	−0.005	0.945	0.943	1,397	0.002	−0.006	−4.39%	-6 bps
	(0.001)	(0.007)				[1.000]		

Table IA.3: Systematic prime-broker relationship channel (OLS instead of WLS)

This table presents the results from a test for excess systematic financial intermediary risk exposure, $\beta^{\text{PBCh.}}$, described in Section 2.1 of the main paper, using OLS instead of WLS (weighted least squares) to estimate a and b in the cross-sectional regression. For details see captions to Table 4 and Table 5 in the paper.

	$\widehat{a}$	$\widehat{b}$	R^2	N	a_{model}	$\widehat{\beta}^{\text{PBCh.}}$	$\frac{\widehat{\beta}^{\text{PBCh.}}}{\sigma(\beta_{Hlds})}$	$\widehat{\beta}^{\text{PBCh.}} \times 2\sigma_{Factor}$
Hedge funds								
β^{FI}	0.018	0.484	0.287	523	0.002	0.015	8.79%	21 bps
	(0.008)	(0.068)				[0.020]		
β^{FI}_{down}	0.078	0.532	0.270	357	0.018	0.060	25.61%	58 bps
	(0.017)	(0.078)				[0.000]		
β^{FI}_{up}	−0.005	0.513	0.295	382	0.011	−0.016	−7.20%	-14 bps
	(0.010)	(0.084)				[0.943]		
Mutual funds								
β^{FI}	−0.002	0.905	0.905	1,834	0.001	−0.004	−3.25%	-5 bps
	(0.001)	(0.010)				[1.000]		
β^{FI}_{down}	0.008	0.919	0.876	1,251	0.008	0.000	0.21%	0 bps
	(0.002)	(0.013)				[0.442]		
β^{FI}_{up}	−0.003	0.940	0.928	1,410	0.001	−0.004	−2.22%	-3 bps
	(0.001)	(0.009)				[0.995]		

Table IA.4: Placebo factors

This table presents the results from a test for excess systematic risk exposure, $\beta^{\text{PBCh.}}$, described in Section 2.1 using alternative placebo factors. Panels A-D present the specification considering a two-factor model comprised of market (MKT) and Fama-French SMB, CMA, RMW, and MOM factors, respectively. For details see caption to Table 4 in the paper.

	$\widehat{a}$	$\widehat{b}$	R^2	N	a_{model}	$\widehat{\beta}^{\text{PBCh.}}$	$\frac{\widehat{\beta}^{\text{PBCh.}}}{\sigma(\beta_{Hlds})}$	$\widehat{\beta}^{\text{PBCh.}} \times 2\sigma_{Factor}$
Panel A: SMB (placebo)								
Hedge funds								
β^{SMB}	0.012	0.507	0.313	523	0.055	−0.043	−12.37%	-27 bps
	(0.017)	(0.046)				[0.995]		
β^{SMB}_{down}	0.104	0.447	0.241	359	0.071	0.033	6.25%	13 bps
	(0.028)	(0.056)				[0.122]		
β^{SMB}_{up}	0.042	0.515	0.269	380	0.048	−0.005	−1.49%	-3 bps
	(0.024)	(0.082)				[0.589]		
Mutual funds								
β^{SMB}	−0.008	0.936	0.957	1,834	0.007	−0.015	−6.78%	-10 bps
	(0.001)	(0.005)				[1.000]		
β^{SMB}_{down}	−0.001	0.936	0.929	1,312	0.009	−0.010	−3.67%	-4 bps
	(0.002)	(0.008)				[1.000]		
β^{SMB}_{up}	−0.013	0.931	0.944	1,381	0.007	−0.020	−7.66%	-10 bps
	(0.002)	(0.009)				[1.000]		
Panel B: CMA (placebo)								
Hedge funds								
β^{CMA}	−0.038	0.501	0.402	523	−0.014	−0.024	−5.18%	-10 bps
	(0.013)	(0.036)				[0.967]		
β^{CMA}_{down}	0.013	0.526	0.385	385	0.011	0.002	0.33%	0 bps
	(0.024)	(0.066)				[0.467]		
β^{CMA}_{up}	0.042	0.529	0.371	343	0.015	0.028	5.03%	9 bps
	(0.023)	(0.048)				[0.118]		
Mutual funds								
β^{CMA}	−0.011	0.951	0.964	1,834	−0.005	−0.005	−1.52%	-2 bps
	(0.001)	(0.005)				[1.000]		
β^{CMA}_{down}	−0.000	0.939	0.904	1,344	−0.001	0.001	0.16%	0 bps
	(0.003)	(0.011)				[0.428]		
β^{CMA}_{up}	−0.008	0.970	0.942	1,348	−0.000	−0.008	−1.60%	-3 bps
	(0.003)	(0.006)				[0.990]		

Table IA.4: Placebo factors (continued)

	$\widehat{a}$	$\widehat{b}$	R^2	N	a_{model}	$\widehat{\beta}^{\text{PBCh.}}$	$\frac{\widehat{\beta}^{\text{PBCh.}}}{\sigma(\beta_{Hlds})}$	$\widehat{\beta}^{\text{PBCh.}} \times 2\sigma_{Factor}$
Panel C: RMW (placebo)								
Hedge funds								
β^{RMW}	0.018	0.499	0.439	523	−0.043	0.061	13.35%	36 bps
	(0.014)	(0.039)				[0.000]		
β^{RMW}_{down}	−0.011	0.452	0.280	326	−0.029	0.018	3.01%	8 bps
	(0.028)	(0.068)				[0.266]		
β^{RMW}_{up}	−0.038	0.438	0.298	407	−0.043	0.006	1.03%	3 bps
	(0.022)	(0.044)				[0.394]		
Mutual funds								
β^{RMW}	−0.008	0.939	0.927	1,834	−0.002	−0.006	−2.55%	-3 bps
	(0.001)	(0.008)				[1.000]		
β^{RMW}_{down}	−0.011	0.944	0.889	1,231	0.008	−0.019	−5.91%	-9 bps
	(0.004)	(0.011)				[1.000]		
β^{RMW}_{up}	−0.033	0.943	0.930	1,476	−0.003	−0.030	−8.88%	-13 bps
	(0.003)	(0.009)				[1.000]		
Panel D: MOM (placebo)								
Hedge funds								
β^{MOM}	0.006	0.662	0.464	523	−0.004	0.010	5.02%	11 bps
	(0.007)	(0.044)				[0.063]		
β^{MOM}_{down}	−0.019	0.609	0.412	341	−0.017	−0.003	−1.04%	-2 bps
	(0.011)	(0.053)				[0.594]		
β^{MOM}_{up}	0.011	0.623	0.447	403	0.002	0.009	3.38%	6 bps
	(0.010)	(0.066)				[0.179]		
Mutual funds								
β^{MOM}	0.005	0.942	0.935	1,834	−0.001	0.006	3.61%	6 bps
	(0.001)	(0.006)				[0.000]		
β^{MOM}_{down}	0.004	0.962	0.968	1,212	0.001	0.003	1.57%	3 bps
	(0.001)	(0.008)				[0.008]		
β^{MOM}_{up}	−0.006	0.933	0.817	1,440	−0.001	−0.005	−3.34%	-3 bps
	(0.002)	(0.013)				[0.998]		

Table IA.5: FI orthogonal to MKT

This table presents the results from a test for excess systematic financial intermediary risk exposure, $\beta^{\text{PBCh.}}$, described in Section 2.1 of the main paper. The table presents a specification considering a two-factor model comprised of market (MKT) and FI factor that has been orthogonalized to MKT in the first step (i.e., FI residuals). For details see caption to Table 4 in the paper.

	$\widehat{a}$	$\widehat{b}$	R^2	N	a_{model}	$\widehat{\beta}^{\text{PBCh.}}$	$\frac{\widehat{\beta}^{\text{PBCh.}}}{\sigma(\beta_{Hlds})}$	$\widehat{\beta}^{\text{PBCh.}} \times 2\sigma_{Factor}$
Hedge funds								
$\beta^{FI^{\perp}}$	0.023	0.547	0.385	523	0.002	0.020	11.62%	18 bps
	(0.005)	(0.052)				[0.000]		
$\beta^{FI^{\perp}}_{down}$	0.049	0.613	0.363	422	0.009	0.040	18.93%	22 bps
	(0.010)	(0.081)				[0.000]		
$\beta^{FI^{\perp}}_{up}$	−0.004	0.651	0.445	296	0.010	−0.014	−5.93%	-8 bps
	(0.010)	(0.049)				[0.912]		
Mutual funds								
$\beta^{FI^{\perp}}$	−0.001	0.926	0.936	1,834	0.001	−0.003	−2.27%	-2 bps
	(0.001)	(0.007)				[1.000]		
$\beta^{FI^{\perp}}_{down}$	0.009	0.927	0.900	1,553	0.005	0.003	2.88%	2 bps
	(0.001)	(0.011)				[0.004]		
$\beta^{FI^{\perp}}_{up}$	−0.005	0.945	0.961	1,148	0.001	−0.007	−4.32%	-4 bps
	(0.001)	(0.011)				[1.000]		

Table IA.6: Systematic prime-broker relationship channel (alternative null factor models for mutual funds)

This table presents the results from a test for excess systematic financial intermediary risk exposure, $\beta^{\text{PBCh.}}$, described in Section 2.1 of the main paper, controlling for alternative factor models on a sample of mutual funds. For details see captions to Table 4 and Table 5 in the paper.

	$\widehat{a}$	$\widehat{b}$	R^2	N	a_{model}	$\widehat{\beta}^{\text{PBCh.}}$	$\frac{\widehat{\beta}^{\text{PBCh.}}}{\sigma(\beta_{Hlds})}$	$\widehat{\beta}^{\text{PBCh.}} \times 2\sigma_{Factor}$
Panel A: Fama French five factors and FI								
Mutual Funds								
β^{FI}	0.001	0.896	0.827	1,834	0.000	0.001	1.49%	1 bps
	(0.001)	(0.011)				[0.089]		
β^{FI}_{down}	0.010	0.907	0.720	1,251	0.005	0.005	4.28%	4 bps
	(0.003)	(0.023)				[0.057]		
β^{FI}_{up}	−0.000	0.926	0.830	1,410	−0.001	0.001	0.88%	1 bps
	(0.001)	(0.016)				[0.263]		
Panel B: MKT, Pastor & Stambaugh illiquidity, and FI								
Mutual funds								
β^{FI}	−0.000	0.928	0.935	1,834	0.002	−0.002	−1.71%	-2 bps
	(0.001)	(0.007)				[0.998]		
β^{FI}_{down}	0.008	0.926	0.887	1,251	0.007	0.000	0.33%	0 bps
	(0.002)	(0.012)				[0.405]		
β^{FI}_{up}	−0.002	0.952	0.950	1,410	0.001	−0.002	−1.48%	-2 bps
	(0.001)	(0.008)				[0.988]		
Panel C: MKT, ΔTED, and FI								
Mutual funds								
β^{FI}	−0.001	0.928	0.938	1,834	0.001	−0.002	−1.93%	-3 bps
	(0.001)	(0.007)				[0.999]		
β^{FI}_{down}	0.007	0.923	0.868	1,251	0.007	−0.000	−0.22%	-0 bps
	(0.002)	(0.013)				[0.556]		
β^{FI}_{up}	−0.002	0.951	0.951	1,410	0.000	−0.003	−1.70%	-2 bps
	(0.001)	(0.007)				[0.995]		

Table IA.7: Prime broker channel (restricted sample)

This table presents the results from a test for excess financial intermediary risk exposure described in subsection 2.2 of the main paper. For details see caption to Table 4 in the paper.
The difference here is that we use a restricted sample of hedge funds for which individual prime broker excess returns are available.

	$\widehat{a}$	$\widehat{b}$	R^2	N	a_{model}	$\widehat{\beta}^{\text{PBCh.}}$	$\frac{\widehat{\beta}^{\text{PBCh.}}}{\sigma(\beta_{Hlds})}$	$\widehat{\beta}^{\text{PBCh.}} \times 2\sigma_{Factor}$
Hedge Funds								
β^{FI}	0.028	0.538	0.376	252	0.005	0.023	13.71%	30 bps
	(0.007)	(0.065)				[0.001]		
β^{FI}_{down}	0.090	0.420	0.195	178	0.021	0.069	26.82%	66 bps
	(0.016)	(0.080)				[0.000]		
β^{FI}_{up}	−0.005	0.637	0.396	190	0.014	−0.018	−8.02%	-15 bps
	(0.012)	(0.085)				[0.932]		

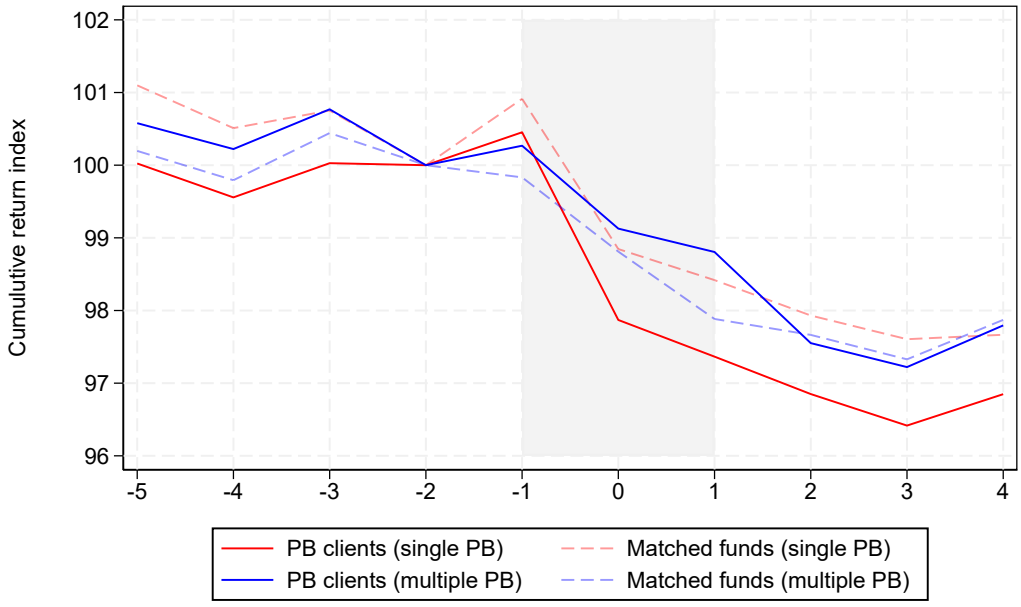
Table IA.8: Event study matched sample

This table presents panel regressions of monthly hedge fund risk-adjusted returns (expressed in %) on various indicator variables and their interactions. For details see caption to Table 6 in the paper. The sample comprises only the hedge funds that were clients of the affected prime brokers two months prior to the respective prime broker event and a matched group of hedge funds not affiliated with these prime brokers. Hedge funds are matched based on the number of prime brokers, style, AUM, and past returns. The sample period runs from January 2000 to June 2021.

	I	II	III	IV	V	VI
Lehman Event	−1.588	−1.588	−1.501	−1.455	−0.783	−0.822
	(1.085)	(1.085)	(1.136)	(1.113)	(1.007)	(0.804)
Lehman Event × Lehman Client	−1.171	0.509	0.556*	0.511	−0.273	0.100
	(0.718)	(0.386)	(0.300)	(0.334)	(0.673)	(0.620)
Lehman Event × Lehman Unique Client		−3.066***	−2.902***	−2.845***	−2.674***	−2.139**
		(0.797)	(0.659)	(0.678)	(0.686)	(0.846)
Lehman Event × Single PB				−0.059	−0.086*	−0.024
				(0.091)	(0.046)	(0.076)
PB Events	−0.649	−0.650	−0.584	−0.542	−0.474	−0.435
	(0.571)	(0.571)	(0.552)	(0.419)	(0.332)	(0.282)
PB Events × PB Client	−0.288**	0.065	0.077	0.046	0.071	0.030
	(0.127)	(0.130)	(0.140)	(0.137)	(0.137)	(0.126)
PB Events × PB Unique Client		−0.534***	−0.454**	−0.408**	−0.298**	−0.283*
		(0.199)	(0.196)	(0.168)	(0.150)	(0.144)
PB Events × Single PB				−0.059	−0.091	−0.042
				(0.268)	(0.211)	(0.178)
Observations	152,676	152,676	151,569	151,569	151,569	151,569
Adjusted R^2	0.014	0.014	0.027	0.027	0.026	0.026
Fund fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	No	Yes	Yes	Yes	Yes
Event window	1 & 1	1 & 1	1 & 1	1 & 1	1 & 2	1 & 3

Figure IA.1: Event study of prime broker shocks

The figure shows, in event time, cumulative equal-weighted hedge fund risk-adjusted return indexes. These indexes comprise returns from clients of the affected prime brokers (solid lines) and those from a matched group of hedge funds not affiliated with these brokers (dashed lines). The three events considered are the failure of Bear Stearns (March 2008), the trading loss scandal of UBS (September 2011), and the trading loss scandal of JP Morgan (April 2012). The shaded region delineates a three-month event window. The indexes are set to 100 two months prior to each event month. The risk-adjusted returns are equal to the constant plus residuals from individual regressions of hedge fund excess returns on the Fung and Hsieh (2004) seven factors. Hedge funds are matched based on the number of prime brokers, style, AUM, and past returns. The figure differentiates between hedge funds with multiple prime brokers (blue shades) and those with only one prime broker (red shades).



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